Essays in International Trade and Development

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Abstract

This dissertation studies different aspects of the interaction between developed and developing countries in global supply chains.

The first chapter studies the matching between importing and exporting firms in global supply chains. I construct a novel dataset that links firm-level information of Indian manufacturing exporters from the CMIE-Prowess database with firm-level information of their US importers from the Longitudinal Business Database. The data highlights three key facts that are consistent with the predictions of a theoretical model featuring sequential production and costly search for high-capability suppliers. First, there is positive assortative matching between US buyers and their Indian suppliers. Second, the strength of positive matching increases with the proximity to final use of the product traded (downstreamness). Finally, matching is stronger - and more sensitive to downstreamness – when the demand elasticity faced by the US buyer is high.

The second chapter examines the effects of export factory work on young girls' school enrollment in the context of the garment industry in Cambodia, which employs primarily young, unmarried women from rural areas. I show that the female siblings of female garment workers who were induced to work in garment exporting sector by their proximity to the factories are one standard deviation more likely to attend school relative to their male siblings. The evidence is consistent with non-unitary household decision-making in which factory work increases the bargaining power of older female siblings within the household.

The third chapter, written jointly with Nathan Nunn, investigates the impact of Fair Trade certification on coffee producers in Costa Rica. We begin by examining a panel of all coffee producers between 1999 and 2010. We find that FT certification is associated with higher export prices equal to approximately 5 cents per pound. Linking the mill-level information on FT certification to individual-level survey data, we find that FT certification does increase incomes, but only for skilled coffee growers and farm owners. There is no evidence that unskilled workers, particularly seasonal coffee pickers, benefit from certification.

Contents

List of Tables

List of Figures

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Chapter 1

Firm-to-Firm Matching Along the Global Supply Chain

1.1 Introduction

Every year, US firms engage in import transactions with more than one million firms from around the world. Together, these transactions span more than one and half million pairs of buyer-supplier relationships. These numbers have grown sharply over the last 20 years. Falling trade costs and improved supply chain management technology have led US firms to outsource parts of the production chain to developing countries. Firms in these countries now perform tasks at many different stages along the global supply chain from the production of basic inputs to complex assembly of parts and manufacturing of final goods. Production fragmentation has contributed to a large increase in the share of US imports from developing countries, from around 28 percent in 1990 to 56 percent in 2012.

As a result, the matching between US buyers and their suppliers in developing countries has become an increasingly important activity for both sides. US buyers invest substantial resources in supplier selection and monitoring to ensure suppliers meet their requirements. Supplier failure can be very costly as shortages of parts cause production delays and quality defects can lead to recalls[1]. For developing country firms, relationships with buyers in developed countries provide not only market access, but also constitute an important channel to access new technologies, management practices and demand information (Egan and Mody, 1992).

Although the matching between buyers and suppliers plays an important role in international transactions, our understanding of this matching process remains limited. In large part, this is because data that allows us to observe detailed information about firms on both sides is not easily available. To shed light on this question, I construct a novel dataset, which links firm-level information on Indian manufacturing exporters from the CMIE-Prowess database with firm-level information on the US firms with whom they engage in trade. To create these matches I use the US import customs transactions from the US Census confidential Linked/Longitudinal Firm Trade Transaction Database (LFTTD). I investigate whether high-performing (large) US firms match with high-performing (large) Indian firms and whether that varies systematically with the position in the supply chain of the Indian firm.

I illustrate the intuition underlying the matching between buyers and suppliers along the production chain in a model of sequential production featuring complementarities. The production of a final good entails the completion of a number of sequential stages. A buying firm (buyer) is in charge of organizing the production of the final good along the value chain. Each stage of production m is controlled by a single supplier who uses the value of production up to stage $m-1$ as an input into stage m production process. Buyers and suppliers are heterogeneous in their capability. The stage revenue function features complementarities between the the capabilities of the buying firm and of the supplier controlling the stage. At each stage, buyers optimally choose the investments in search for high-capability suppliers to control the production process. A key feature of the model is that the marginal contribution to revenue of the stage-m supplier is increasing with the stage of production m. This implies that the marginal benefit of search for the

[1]See Beil (2010) for a comprehensive discussion of the process of supplier selection.

high-capability supplier increases with the stage of production. The model delivers three main predictions. The optimal amount of investment in supplier search, and hence the strength of positive assortative matching between buyers and suppliers increases with (1) the stage of production; (2) the elasticity of demand faced by the buyer; (3) the stage of production relatively more when the buyer faces more elastic demand. The third prediction implies that the investment in search for the high-capability suppliers is more sensitive to the stage of production when the buyer is selling a less differentiated product.

I test the model predictions in the matched data. I use US and Indian firm size as the empirical counterparts to the buyer and supplier capability in the model, and the Antràs et al. (2012) product "downstreamness" measure to capture the position in the production chain of the Indian supplier. I employ two empirical strategies. In the first empirical strategy, I calculate the average size of US firms buying a given product from an Indian firm, and examine how that average varies with Indian firm size. I find that the estimated elasticity of average US firm size with respect to Indian firm size is positive and around 0.24. Consistent with the first prediction of the model, I find that the magnitude of the elasticity increases with the downstreamness of the product traded. When the product traded is close to final consumption (as is the case for consumer products), the elasticity is around 0.5, so a doubling of Indian firm size is associated with an increase in average buyer size of 50%. The sorting on size of buyers and suppliers trading very upstream products is much weaker. Here, the estimated elasticity of US buyer size with respect to Indian firm size is close to zero. The relationships are robust to controlling for other product characteristics that are correlated with upstreamness. The last two predictions of the model also find support in the data. Using the Broda and Weinstein (2006) estimates of import demand elasticities to obtain a measure for the demand elasticity faced by US firms, I find that the buyer-size elasticity is on average larger, and increases more rapidly with the stage of production, when Indian firms deal with US buyers selling less differentiated products.

In the second empirical strategy, I estimate a model of selection into a trading relationship at the Indian firm, US firm, product level as a function of US and Indian firm size, while controlling for other product and firm characteristics available from the matched data. Consistent with the estimated buyer-size elasticities, I find that the probability of engaging in trade with larger US buyers is increasing with the size of the Indian supplier, and that this probability declines with the distance from final use of the product traded. The results are again broadly consistent with the model's predictions for the influence of demand elasticity.

In focusing on the complementarity between buyer and supplier capability in global production networks this paper is related to the extensive literature emphasizing the complementarity of inputs in production and its extensions to sequential production settings (Sattinger (1975), Milgrom and Roberts (1990), Kremer (1993), Maggi and Grossman (2000), Garicano (2000), Antràs et al. (2007), Verhoogen (2008), Kugler and Verhoogen (2012), Antràs and Chor (2013), Costinot et al. (2013)). A common feature is that a supermodular production function where the marginal product of one agent is increasing in the productivity of the other agents leads to positive assortative matching in equilibrium. Agents with similar productivity work together. When production is sequential, the equilibrium allocation dictates that higher productivity agents control later stages of production. Mistakes at the end of the production chain destroy higher-valued intermediate inputs than in earlier stages (Sobel (1992), Kremer (1993)). In international trade, a growing literature has studied the implications of complementarities and sequential production for the patterns of specialization and trade flows between countries. Costinot et al. (2013) build a theoretical model to show that when production is sequential and subject to mistakes, countries with higher income per capita which have lower probability of mistakes at all stages of production specialize in the later stages of production, and low-income countries specialize in the earlier stages of production. Antràs and Chor (2013) build a theoretical model to study how the sequentiality of production shapes the optimal ownership structure (integration versus outsourcing) between final-good producers and their various suppliers along the value chain. Their model derives predictions for how property rights should be allocated along the production chain and emphasize a key role played by the elasticity of demand faced by the final-goods producer for the optimal allocation.

This paper is also directly related to the extensive theoretical and empirical literature in international trade emphasizing firm heterogeneity in differentiated product markets[2]. In particular, this paper is part of an emerging strand of the literature examining the matching of importing and exporting firms and the implications of two-sided heterogeneity in international trade. The existing studies use customs-level data in which buyers and sellers can be identified in each transaction (Blum et al. (2009), Blum et al. (2012), Bernard et al. (2013))[3]. Using variables constructed from customs data to measure firm size, these studies find that small exporters trade with large importers, while large exporters are able to reach both large and small importers.

This paper contributes to our understanding of firm matching in the global economy in three main ways. First, because this paper matches customs-level data with firm-level data on buyers and sellers, it is able to employ an actual measure of firm performance for both sides of the transaction and not rely solely on customs-level variables to obtain buyer and seller characteristics, such as number of partners and total value of trade. Second, this paper documents firm matching patterns between Southern suppliers (Indian firms) and their buyers in the North (US firms), and the existing literature has focused largely on South-South or North-North trade. Finally, this paper explores how the sorting patters of buyers and suppliers vary with product characteristics, and finds that there is substantial heterogeneity. It is this last distinction that is the most important. Both the model and empirical results here suggest that how buyers and suppliers match with each other are far from uniform across the product space. At a minimum, this matching depends on the

[2]See Melitz and Redding (2014, Forthcoming) and Bernard et al. (2012) for a review of theoretical and empirical contributions.

[3]Other recent papers exploring buyer-supplier relationships are Carballo et al. (2013) and Eaton et al. (2012). Carballo et al. (2013) use customs data from Costa Rica, Ecuador and Uruguay to explore the export margins of firms. Decomposing exports across different margins, they find that the buyer extensive margin is at least as important as the firm and the product extensive margins for aggregate bilateral exports as well as the firm's product extensive margin for firms destination-specific exports. Eaton et al. (2012) consider exports of Colombian firms to US importers, and use the confidential US customs data containing US imports from Colombian exporters. They develop a model of search and learning in which sellers learn from a given match about their productivity in a given market, and this knowledge affects their subsequent search behavior for new buyers.

position of the product in the supply chain and the elasticities of demand faced by the buying firm, even for a given country pair. A better understanding of how the costs and benefits of establishing a buyer-supplier match vary across different types of products and trade relationships is needed to be able to explain the assortative matching patterns between firms in the global economy.

The paper proceeds as follows. The next section describes the theoretical framework used to derive empirical predictions regarding the matching of buyers and sellers along the value chain. Section III describes the data sources and the construction of the matched dataset of Indian suppliers and their US buyers. Section IV presents the empirical strategy and establishes the main empirical results. Section V concludes.

1.2 A Model of Sequential Production

In this section, I provide a stylized theoretical framework to guide the subsequent empirical analysis. I consider a sequential production process in which each stage of production is controlled by a different supplier. A final-goods producer (buyer) with capability θ is in charge of organizing the production chain. In each stage, the buyer chooses the capability of a supplier to occupy a given stage of production. One can interpret the supplier's capability as its ability to meet the buyer-specific requirements for price, quality and delivery. To illustrate the trade-off faced by the buyer in choosing a supplier at different stages of production, I introduce supplier search costs. More precisely, I assume that before trade between the buyer and the supplier takes place, the buyer needs to invest resources in a search and screening to identify whether suppliers have high-capability, and are able to meet its requirements. Higher investments in screening decrease the likelihood that the buyer engages in a relationship with a low-capability supplier. The main trade-off faced by the buyer along the value chain is between investing more resources in supplier search and increasing the revenue generated in a given stage.

I derive the argument in four stages. First, I derive the marginal contribution to final revenue of a supplier at stage m. Second, I show that the marginal contribution of the supplier occupying the stage of production m increases with the stage of production, m. Third, to illustrate the trade-off faced by final goods producers in choosing suppliers along the value chain, I introduce search costs for high-quality suppliers. I show that the marginal benefit of search is increasing with the stage of production, and is increasing relatively more for products in which the final buyer faces a high elasticity of demand.

1.2.1 Sequential Production

Assume that the production of a final good entails the completion of number of production stages, which are indexed by j. Each stage of production is controlled by a different supplier. Production is sequential - stage j cannot commence until stage $j-1$ has been completed. Let q_j be the capability of a supplier controlling stage j. The volume of production up to stage m is given by

$$q(m) = \theta \prod_{j=1}^{m} q_j I(j) \tag{1.1}$$

j is increasing with the stage of production. $I(j) = 1$ if supplier j enters the production chain after stages $j' < j$ have been completed and 0 otherwise. A final-goods producer with capability θ is in charge of organizing the production chain. Note that it is necessary to impose $q_j > 1$ for the production to be increasing along the value chain.

The sequential nature of production implies that downstream suppliers are useless unless upstream stages have been completed. In fact, it is useful to express the technology in equation (1.1) in differential form. The marginal contribution to output of the supplier at stage m is given by:

$$q(m) - q(m-1) = \theta \prod_{i=1}^{m} q_i - \theta \prod_{i=1}^{m-1} q_i = \theta (\prod_{i=1}^{m-1} q_i) I(m)(q_m - 1) \tag{1.2}$$

The supplier at stage m uses the value of production up to stage m, $q(m-1)$ as an input to the stage-m production process, where it combines this input with its own capability q_m. Note that the importance of supplier m's capability to total output is increasing with the value of production accumulated up to stage m ($q(m-1)$), and hence the stage of production.

1.2.2 Preferences

The final good is a differentiated variety in the eyes of the consumer and belongs to an industry in which firms produce a continuum of goods. Consumer have preferences that feature a constant elasticity of substitution across these varieties, equal to $1/(1-\rho) > 1$

$$U = (\int_{\omega \in \Omega} q(\omega)^{\rho} d\omega)^{\frac{1}{\rho}}$$

where $\rho \in (0,1)$, $q(\omega)$ is the quality-adjusted output of variety ω and Ω is the set of varieties consumed.

Under this class of preferences, consumer behavior can be modeled in terms of the aggregate quantity of varieties consumed and an aggregate price. A firm producing variety ω will face a demand $q(\omega) = Ap(\omega)^{\frac{-1}{1-\rho}}$ where $A > 0$ is the industry demand shifter, which the firm treats as exogenous. The revenue function of the final goods producer of variety ω will be given by $r(\omega) = A^{1-\rho}q^{\rho}$.

Substituting the production technology defined in equation (1.1), the total revenue generated by the buying firm up to stage m is given by:

$$r(m) = A^{1-\rho}\theta^{\rho}q(m)^{\rho} \tag{1.3}$$

The incremental contribution to final revenue of the stage-m supplier is given by

$$r(m) - r(m-1) = r'(m) = A^{1-\rho}\theta^{\rho}q(m)^{\rho} - A^{1-\rho}\theta^{\rho}q(m-1)^{\rho} = r(m-1)(q_m^{\rho} - 1) \tag{1.4}$$

Note that $r'(m)$ is increasing with the stage of production because $q(m-1)$ is increasing along the production chain.

1.2.3 Supplier Search

In each stage of production, the buyer must search for a supplier to perform the activities required by the buyer in that given stage. For simplicity, assume that each stage of production is populated by two types of suppliers: high-capability suppliers (q_H) and low-capability suppliers (q_L). To identify the H types, a buyer needs to invest resources in screening suppliers. Assume the screening costs are of the form $c(p)$, where p is the likelihood that the supplier is of type H. Assume that $c(p)$ is convex in p, $c'(p) > 0, c''(p) > 0$.

The buyer and the supplier bargain over the surplus generated in a given stage of production, and the buyer always obtains a share β of the stage surplus. The outside option of the supplier is normalized to zero. Assume that the buyer searches *sequentially* for suppliers along the value chain to maximize the marginal contribution to total revenue of supplier m. This assumption holds if different divisions within the buying firm are responsible for purchasing at different stages of production, and the division in charge of stage m starts searching for stage-m suppliers after the searches in previous stages have been completed. The buyer's optimization problem is to choose the optimal amount of investment in search to carry out at stage m, p_m, to maximize expected stage profits:

$$max_{p_m}\beta[p_m r'_H(m) + (1-p_m)r'_L(m) - c(p_m) \tag{1.5}$$

Substituting the expression for marginal contribution to revenue in equation (1.4), gives

$$max_{p_m}\beta[p_m r(m-1)(q_H^\rho - 1) + (1-p_m)r(m-1)(q_L^\rho - 1)] - c(p_m) \tag{1.6}$$

At each stage, the buyer chooses the amount of investment in supplier search such that the marginal cost of search equals the marginal benefit of search:

$$c'(p_m) = \beta A^{1-\rho}\theta^\rho q(m-1)^\rho[q_{mH}^\rho - q_{mL}^\rho] \tag{1.7}$$

The marginal benefit of search is the difference in the stage revenues obtained with the high-capability supplier and with the low capability supplier respectively. In the next subsection, I will show that the marginal benefit of search increases with the stage of production.

1.2.4 Empirical Predictions

First, note that the marginal benefit of search for high-capability suppliers is larger for higher θ buyers. High-capability suppliers are more valuable to high-θ buyers because the because the revenue function exhibits complementarities in the buyer and supplier capability. This implies that higher-capability buyers will be more likely to engage in search than lower capability buyers at all stages of production. This is the force that generates positive assortative matching at all stages of the supply chain.

$$\frac{\partial c'(p_m^*)}{\partial \theta} = \rho\beta A^{1-\rho}\theta^{\rho-1}q(m-1)^{\rho}[q_{mH}^{\rho} - q_{mL}^{\rho}] > 0 \tag{1.8}$$

The partial derivative of the optimal amount of search at stage m with respect to θ is also increasing with ρ, and hence $1/(1-\rho)$, the elasticity of demand faced by the buyer. These two results imply high-capability buyers are more likely to work with high-capability suppliers in products where the elasticity of demand faced by the buyer is high.

Second, note that the marginal benefit of search is increasing with the stage of production. Differentiating equation 1.7 with respect to $q(m-1)$, the value of production up to stage m yields

$$\frac{\partial c'(p_m^*)}{\partial q(m-1)} = \rho\beta A^{1-\rho}\theta^{\rho}q(m-1)^{\rho-1}[q_{mH}^{\rho} - q_{mL}^{\rho}] > 0 \tag{1.9}$$

The elasticity of final demand faced by the buyer also plays a role in shaping how the investments in search change with the stage of production. Higher demand elasticities magnify the investments in supplier search by final goods producers.

Summarizing, the model presented above delivers three main empirical predictions regarding the likelihood that high-capability buyers engage in trade with high-capability suppliers, as a function of the characteristics of the product traded and the nature of demand faced by the buyer.

Define *positive assortative matching*(PAM) as a high-capability (higher θ) buyer engaging in trade with the high-capability q_H supplier. The likelihood that these two types of firms match, which is a function of the marginal benefit of search, denotes the strength of PAM. Equation 1.9 gives the following predictions:

1. The strength of PAM increases with the stage of production, m
2. The strength of PAM is increasing with the elasticity of demand faced by the buying firm, ρ
3. The strength of PAM increases with the stage of production relatively more when elasticity of demand faced by the buying firm is high

To test the model predictions, I use a novel matched dataset of relationships between Indian manufacturing suppliers and US buyers which I describe in the next section. I describe in detail how the model parameters are measured in the data.

1.3 Data and Matching

The challenge in observing the matching patterns predicted by the model is to link trade transactions so that we can observe detailed characteristics of firms on *both* sides of the transaction. The innovation of the dataset used this paper comes from the matching of a sample of manufacturing exporting firms from the CMIE-Prowess database with US Census Linked/Longitudinal Firm Trade Transaction Database (LFTTD)[4]. The matching allows us for the first time to identify the characteristics of firms who engage in a trade transaction.

LFTTD is itself a matched dataset, and links the Foreign Trade Data (FTD) from the US customs with the Longitudinal Business Database (LBD) (Bernard et al., 2010). The FTD is assembled by the US Census Bureau and US Customs and Border Protection (CBP) and captures all international trade transactions (imports and exports) carried out by US firms

[4]For detailed description see http://econ.duke.edu/tcrdc/census-data/mixed/lfttd-overview.

from 1992 until present. For each import and export transaction, the dataset records the product classification (at the HS 10-digit level), the value and quantity transacted, the date of the shipment, the destination (or source) country, the transport mode, and whether the transaction takes place at arm's length or between related parties[5].

The US Census Bureau's Longitudinal Business Database (LBD)[6] records annual employment, payroll, industry classification, and survival information for the universe of establishments in the non-farm private sector with at least one paid employee starting in 1976. The unit of observation is an establishment which is defined as a single physical location where economic activity takes place. Each establishment has a corresponding firm identifier. US firms can own a single establishment or multiple establishments. Since the FTD records the US firm (not the establishment) undertaking a foreign transaction, the links between LBD and FTD are done at the firm level. This means that it is only possible to assign foreign transactions to a US firm rather than a US establishment. On average 80% of trade transactions by value can be matched with importer information in LBD (Bernard et al., 2010).

I match the LFTTD with the CMIE-Prowess database of Indian firms. The CMIE-Prowess database of Indian firms provides income/expenditure (including the amount of revenue generated from exports) and balance sheet data for medium and large firms in India. The companies account for close to 70 percent of the economic activity in the organized industrial sector India and close to 60 percent of exports.

1.3.1 Matching LFTTD with Prowess

The matching between Prowess and LFTTD is possible because Prowess contains the name and the address of Indian firms. While the LFTTD does not store the full name of exporting

[5]"Related-party", or intra-firm, trade refers to shipments between US companies and their foreign subsidiaries as well as trade between US subsidiaries of foreign companies and their affiliates abroad. For imports, firms are "related" if either owns, controls or holds voting power equivalent to 6 percent of the outstanding voting stock or shares of the other organization.

[6]See Jarmin and Miranda (2002) for detailed description.

firms, it contains a variable called manufacturer's ID (manufid) which contains parts of an exporting firm name and address.The US Customs provides detailed instructions on how to construct the manufid variable[7]. The LFTTD manufid variable has only recently been used in academic research papers to identify buyer-supplier relationships (see Eaton et al. (2012), Kamal and Krizan (2013), Kamal and Sundaram (2012)). I conduct the matching in 4 steps. First, I start with an initial sample of approximately 4,900 manufacturing firms with positive exports in at least one year between 1995 and 2007, as reported in the Prowess database. Second, I match the name part of the manufacturer's ID in LFTTD with the names of Prowess exporters. Third, I construct a location matching score for the manufacturer's ID based on an indicator variable which is equal to 1 if the city of the exporter as reported in LFTTD corresponds to the set of cities reported in Prowess. Finally, I construct a product matching score based on an indicator variable which checks whether the product shipped by Indian firms is the same as the product recorded in the customs data. I drop all the manufacturer's ID assigned to an Indian firm with location and product matching scores of less than 90%. I also drop from the matched data any Indian firms who have less than 5 transactions in total to eliminate accidental exporters from the database.

1.3.2 Summary of the Matched Data

The matched dataset spans around 128,400 trade transactions and 7,400 importer-exporter relationships between 1995 and 2007. I collapse all the transactions between an Indian exporter and a US importer at the year and product level (HS-4). The characteristics of the US and Indian firms in a given year are derived from the LBD and Prowess respectively.

The number of Indian manufacturing firms in the matched sample is approximately 1050. This represents around 20% of the number of exporting firms from the initial sample of Indian exporters[8]. Importantly, the dataset contains only those Indian manufacturing

[7]For example, a company with the name of Cosmo Garments with registered office address JLB Road 229, Mysore, Karnataka state should appear in LFTTD as INCOSGAR22MYS in LFTTD.

[8]The match rate in terms of the number of firms is comparable to India's aggregate trade with the US. The US represents roughly 10% (13% excluding oil) of India's exports to the world.

Table 1.1: *US Importing Firms: Summary Statistics*

	Firm size (total employment	Value of yearly imports	Firm age (years)	Number of products imported (HS-10)	Number of suppliers in a given product (HS-4)	Share of Firm Employment		
						Whole-sale	Retail	Manufac-turing
Mean	5,816	$ 234,000,000	12.9	129	30	0.5	0.1	0.3
St. Dev	35,033	$ 1,540,000,000	8.0	558	117	0.5	0.3	0.4

Notes: The table presents summary statistics for the US firms in the matched data. Total number of firms (rounded) is 4100. Mean of ln(employment) is 4.41 and the standard deviation of ln total employment is 2.92.

firms which trade directly. Although firms might record positive exports in Prowess, they may be exporting indirectly through Indian intermediary firms. These firms will not be part of the matched dataset.

On the US side, the matched sample contains around 4,100 US importers. This represents around 2 percent of the total number of importers which was estimated to be around 184,000 in 2011. Table 1.1 presents the summary statistics for the sample of US firms.

The distribution of activities of US firms in the sample is roughly similar to the patterns documented in earlier studies by Bernard et al. (2009). Studying the differences between intermediaries (categorized as wholesalers and retailers) and other types of firms, Bernard et al. (2009) find that more than 42 percent of importing firms are "pure" wholesalers (firms with 100% of employment in wholesaling), but they account for only 15 percent of import value. "Pure" retailers (firms with 100% of employment in retailing) are less prevalent and smaller than wholesalers and account for only 1% of import value. More than 50% of import value is accounted for by "mixed" firms, firms with operations that span wholesale or retail and other sectors. "Mixed" firms are very rare, accounting for only 5% of the number of importers, but they are substantially larger, trade more products, trade with more countries, and are more likely to engage in related-party trade. Under their classification, more than half of the US firms in the dataset are "pure" wholesalers (2,200 or 53%), 4% are "pure" retailers, 17% (700) are pure manufacturing firms and 17% (700) are mixed firms out of which 500 are firms with predominant manufacturing activities and the rest are firms with predominant intermediation activities. I use the dummies for the firm types as controls in the regression. As alternative controls to capture the types of activities of US firms, I also construct measures of intensity of various types of activities, such as wholesale, retail and manufacturing intensity. I do this by dividing employment in these activities by total employment.

The average number of US buyers per firm is 3, and per firm-product is 1.4. The average relationship duration is 2.8 years. The total number of products (at HS-4 level) in the sample is approximately 700. The top products in the sample are apparel and textiles, chemicals and foodstuffs and which are representative of Indian exports to the US.

1.3.3 Measuring Key Parameters of the Model

The predictions of the theoretical model center around three parameters: firm capability, stage of production, and elasticity of demand faced by the buying firm. I now describe how I proxy each of these variables empirically.

US and Indian Firm Capability

There are clearly many dimensions to the matching and selection process between buyers and suppliers in the global production chain. The model of sequential production developed in Section 2 focuses on the matching of buyers and suppliers on one key dimension: firm capability. In the data, I proxy this with firm size, as measured from the Prowess for Indian firms and LBD for US firms. I use total firm revenues to measure firm size in Indian and total firm employment to measure firm size in the U.S. Firm size is positively correlated with firm capability in heterogeneous firm trade (HFT) models in international trade (Melitz (2003) and its numerous extensions). In these models, ex-ante homogeneous firms pay a fixed cost to receive a "capability"[9] draw, φ, from an exogenous distribution. φ uniquely

[9] In Melitz (2003) higher "capability" entails higher productivity, or lower marginal costs of production. In the extensions to the Melitz model to include endogenous quality choice, higher capability is associated with higher product quality and high prices

determines pricing, revenues, and profits, generating ex-post firm heterogeneity. Under both CES and linear demand and monopolistic competition, higher φ firms will earn higher revenues, make higher profits and hire more workers.

Using firm size (as opposed to calculated TFP) to proxy for firm capability abstracts from some of the well-known difficulties of measuring TFP in the presence of quality heterogeneity of inputs and outputs (see Loecker and Goldberg (2014) for extended discussion). Firm size has the advantage of being easily measurable in the data for both US and Indian firms. I use two different measures of size as the empirical measures of firm productivity dictated by data availability in the two datasets: total firm revenues for Indian firms and firm total employment for US firms. Both measures of firm size move in tandem with the theoretical concept of productivity that underpins the HFT models, as dicussed above.

I follow Haltiwanger et al. (2013) and calculate *US firm size* as the sum of employment at all establishments owned by the firm from LBD. The size of single-unit establishments will be employment at the single establishment owned by the firm.

I also consider alternative measures of US firm size which have been used by existing studies using customs data. I calculate the total value of imports as one alternative measure. This is obtained by summing over all the import transactions assigned to a US firm in a given year in the customs data. I calculate this measure both at the product level and at the firm level. I also calculate the total number of suppliers at the firm-year and firm-product-year level by counting the unique number of manufacturer's IDs with whom the US firm trades. Finally, I combine total firm employment calculated from LBD and the total value of imports from LFTTD to construct a measure of import intensity, the value of imports per employee. This variable allows us to quantify the degree to which firms are specialized importers and distribute the products imported to other firms, or they are using the imports in production.

I measure *Indian firm size* with total revenues reported in the Prowess database. In the sample of all exporters from Prowess, the mean firm size is 3855.77 Million Rupees (6.35 in logs) while the median is 596.65 Million Rupees (6.35 in logs). The standard deviation is 40763.2 Million Rupees (1.7 in logs). In the matched sample, the mean firm size in logs is

6.74 and the standard deviation is 1.6.

Stage of production, m

The model predicts that the strength of assortative matching increases with the stage of production, m. To obtain a measure of the stage of production of the Indian firm, I use the product upstreamness measure developed by Antràs et al. (2012). This measure gives the average distance from final use of a given product and was constructed using the information from 2002 Input-Output tables of the United States from the BEA. More precisely, the upstreamness of a given industry is a weighted average of the distance from final use at which the industry's output is used, with the weight equal to the share of industry's use at each stage from total industry output. I use the BEA concordance between 2002 Input-Output commodity codes and the foreign trade harmonized codes.

Consider an economy with i. The value of gross output (Y_i) equals the sum of its use as a final good (F_i) and its use as an intermediate input to other industries (Z_i)

$$Y_i = F_i + Z_i = F_i + \sum_{j=1}^{N} d_{ij} Y_j$$

where d_{ij} is the dollar amount of sector i's output needed to produce one dollar's worth of industry j's output.F_i is composed of personal consumption and private fixed investment. This identity can be iterated which results in industry i's output being expressed as an infinite sequence of terms which reflect the use of this industry's output at different positions in the value chain, starting with final use:

$$Y_i = F_i + Z_i = F_i + \sum_{j=1}^{N} \sum_{k=1}^{N} d_{ik} d_{kj} F_j + \sum_{j=1}^{N} \sum_{k=1}^{N} \sum_{l=1}^{N} d_{il} d_{lk} d_{kj} F_j + ...$$

Antràs et al. (2012) suggest calculating an industry i's upstreamness measure can be obtained by dividing each of the terms in the expression above by the total output Y_i and weighing each term by the distance from final use plus 1

Figure 1.1: *The Upstreamness of US Manufacturing Industries: Least and Most Upstream Industries*

US IO2002 Industry	Upstreamness
Automobile (336111)	1.000
Light truck and utility vehicle (336112)	1.001
Nonupholstered wood household furniture (337112)	1.005
Upholstered household furniture (337121)	1.007
Footwear (316200)	1.007
Motor home (336213)	1.012
Truck trailer (336212)	1.017
Manufactured home (mobile home) (321991)	1.019
Women's and girls' cut and sew apparel (315230)	1.024
Mattress (337910)	1.029
Plastics material and resin (325211)	3.571
Copper rolling, drawing, extruding and alloying (331420)	3.611
Alkalies and chlorine (325181)	3.611
Carbon and graphite product (335991)	3.748
Fertilizer (325310)	3.762
Alumina refining and primary aluminum (33131A)	3.814
Other basic organic chemical (325190)	3.853
Secondary smelting and alloying of aluminum (331314)	4.064
Primary smelting and refining of copper (331411)	4.355
Petrochemical (325110)	4.651

$$U_i = 1 \cdot \frac{F_i}{Y_i} + 2 \cdot \frac{\sum_{j=1}^{N} F_j}{Y_i} + 3 \cdot \frac{\sum_{j=1}^{N}\sum_{k=1}^{N} d_{ik} d_{kj} F_j}{Y_i} + 4 \cdot \frac{\sum_{j=1}^{N}\sum_{k=1}^{N}\sum_{l=1}^{N} d_{il} d_{lk} d_{kj} F_j}{Y_i} + ...$$

The U_i measure ranges from 1, where all of the industry's output is used in final consumption, to 4.5 where all of an industry's output is used as inputs for industries who are on average 4 steps removed from final use, since those industries serve as inputs to more downstream industries and so on. The mean of the upstreamness variable U_i is 2.09 and the standard deviation is 0.85. Figure 1.1 presents the industries with the lowest and highest values of upstreamness respectively. Consumer products have low values of upstreamness since their output is allocated to personal consumption expenditures while chemicals, plastics and petrochemicals have very high values of upstreamness since all of the output in these industries serves as intermediate inputs for other intermediate input industries and so on.

Buyer Demand Elasticity, $1/(1-\rho)$

Testing the predictions of the model entails obtaining a measure of the elasticities of demand faced by US buyers. I do this using the NAICS industry classification of the buyer establishments available from LBD and the Broda-Weinstein import demand elasticities. I use the concordance between the HS-10 product classification (at which level the Broda-Weinstein elasticities are estimated) and the NAICS industry classifications from (Pierce and Schott, 2012).

The concordance between NAICS industry codes and HS-10 codes is available only for manufacturing industries. However, almost three quarters of the sample is comprised of US buyers who are classified as wholesalers, retailers or mixed-intermediary firms. Unlike manufacturing firms, these buyers will sell the same product in the US market as the product traded with the Indian firm. For buyers who are intermediaries, I assume that the elasticity of demand they face is equal to the Broda-Weinstein elasticity of the product they trade. For buyers who are classified in manufacturing, the elasticity of demand is the average demand elasticity of their NAICS industry which is obtained averaging the elasticities of the HS codes corresponding to their NAICS concordance.

1.4 Empirical Strategy

1.4.1 Size Elasticities

I start by documenting average correlations between the Indian firm size and the average size of the US firms with whom they engage in trade. To do this, I create a measure of "exposure" to US firm characteristic c (such as total employment, total value of imports, etc) for a given exporting firm i in product p in year t, E^c_{ipt}. The exposure to US firm characteristic c is the weighted average of the characteristic c of importers m with whom firm i trades in product p. More precisely:

$$E^c_{ipt} = \sum_{m \in i} \frac{X_{impt}}{X_{ipt}} c_{mt}$$

where m denotes as US importer, c_{mt} denotes importer m's characteristic of interest at time t (such as total employment); X_{impt} is the value of exports from exporter i to importer m in product p in year t and X_{ipt} denotes exporter i's total value of exports of product p in year t. The exposure measure takes into account both the intensive and extensive margins of Indian firm's trade with US firms. The characteristics of those buying firms who account for more of exporter's US revenues in product p receive a higher weight in the exposure measure calculation. I also calculate an "extensive" measure of exposure to US firm characteristics as the simple average of buyer characteristics. In that calculation, each buyer has the same weight, irrespective of its trade with p at time t. The results presented in the next section are robust to employing this alternative measure of exposure, and the magnitude of the coefficients is similar.

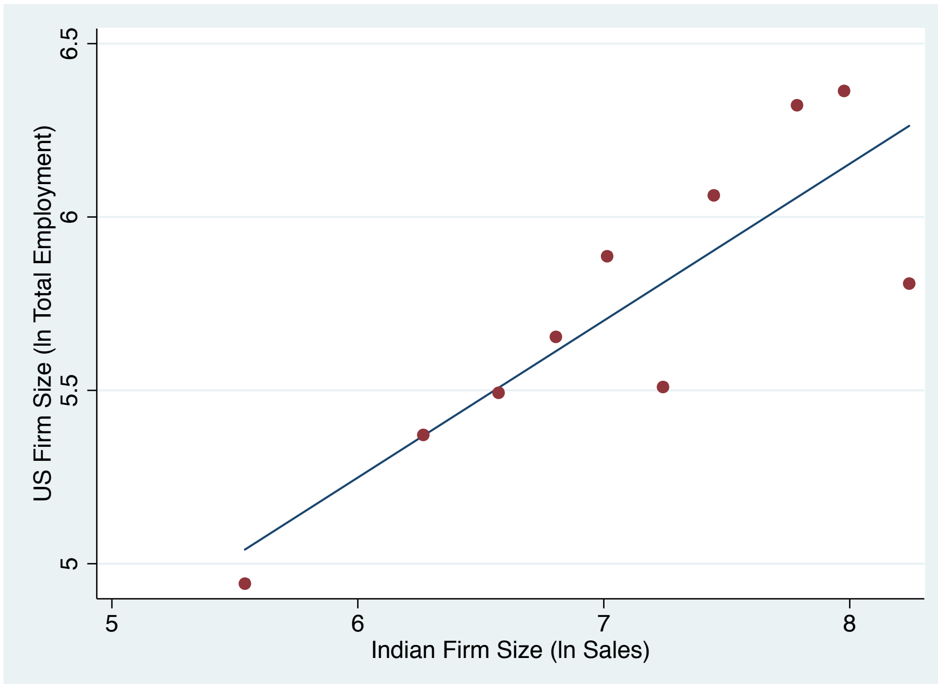
Exporter i's exposure to US firm size as measured by total employment (Emp_{mt}) will be the weighted average of the average employment of US firms buying product p from exporting firm i in year t. Because the exposure measure is calculated at the Indian firm, product level, firms exporting multiple products may have different exposures to US firm size for each product, if the set of buyers buying each product is different.

$$E_{ipt}^{emp} = \sum_{m \in i} \frac{X_{impt}}{X_{ipt}} Emp_{mt}$$

Figure 1.2 presents the relationship between Indian firm size S_{it} (on the x-axis) and the exposure to US firm employment in a given product, E_{ipt}^{emp}, (on the y-axis) non-parametrically, in a binned scatter plot. To construct the binned scatter plot, I first residualize S_{it} and E_{ipt}^{emp} with respect to HS 4-digit product fixed effect using an OLS regression estimated on the whole sample. I then divide the residuals of S_{it} into ten equally-sized bins and plot the means of E_{ipt}^{emp} residuals in each bin against the mean of S_{it} residuals. The relationship is positive suggesting that larger Indian firms tend to engage in relationships with larger US firms in the sample.

To explore how the relationship between Indian firm size and their exposure to US firm size varies along the supply chain, I construct the binned scatter plot in two subsamples.

Figure 1.2: *The Relationship Between Indian Firm Size and the Average Size of Its US Buyers*



The first subsample is comprised of Indian firms who trade products in the bottom 25th percentile of product upstreamness (close to final consumption), and the second subsample is composed of firms trading products in the top 75th percentile of product upstreamness. Figures 1.3 and 1.4 present the corresponding binned scatter plots for the two subsamples. The plots suggest that the positive relationship between Indian firm size and average size of US firms with whom they interact in a given product is driven by products who are close to final use (essentially consumer products). This relationship is much weaker when Indian firms export very upstream products, since large and small Indian firms tend to interact with US firms of the same size on average.

Turning to regression analysis, the baseline estimation equation is the following

$$ln\ E^{c}_{ipt} = \alpha_t + \alpha_p + \beta_1 ln\ S_{it} + \varepsilon_{ipt} \tag{1.10}$$

where α_t are year fixed effects (1995-2007), α_p are product (HS-4) fixed effects, S_{it} is the size (total revenues) of Indian firm i in year t and E^{c}_{ipt} is firm i's exposure to measures of US firm

Figure 1.3: *The Relationship Between Indian Firm Size and the Average Size of Its US Buyers – Downstream Products*

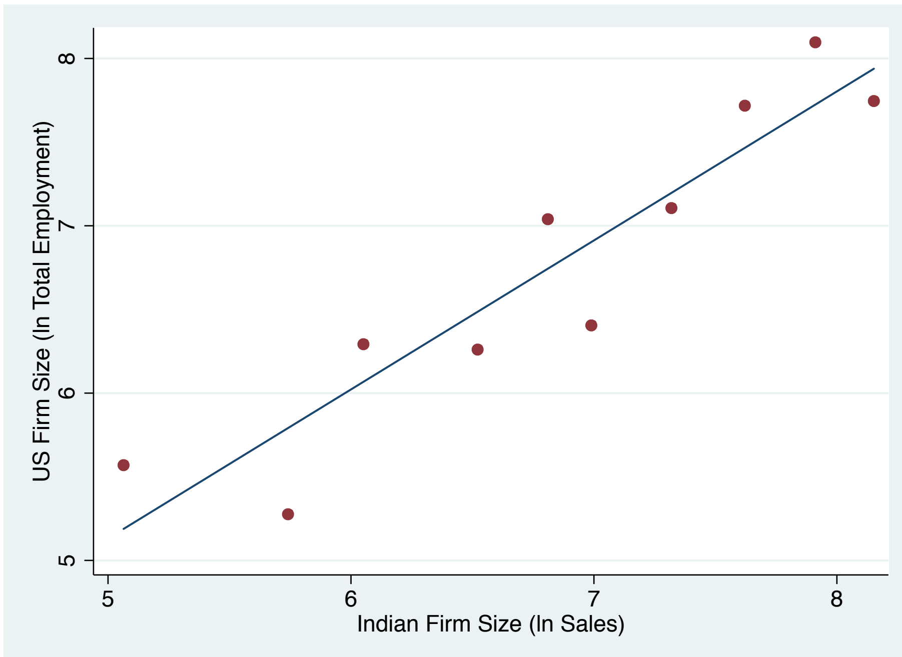
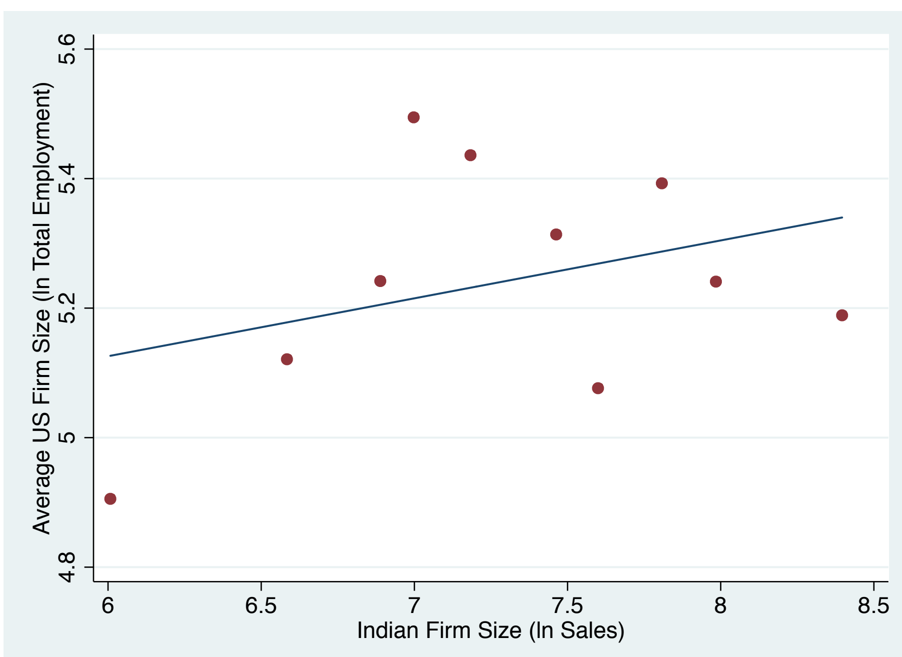


Figure 1.4: *The Relationship Between Indian Firm Size and the Average Size of Its US Buyers – Upstream Products*



size in product p at time t. The product fixed effects α_p control for systematic differences across products in the size of exporters and their exposure to US firm characteristics trading a given product. The year fixed effects control for shocks common to all Indian firms which may affect their trade with US firms and their exposure to US firm characteristics.

The coefficient β_1 measures the elasticity of average US buyer size with respect to Indian firm size within a given product. That is, β_1 measures the percentage change in the average size of the US buyer corresponding to a 1% increase in Indian firm size. A positive and significant β_1 suggests that larger Indian exporters tend to trade with larger US importers.

To test the first prediction of the theoretical model and explore how the buyer size elasticity varies with the stage of production of the Indian firm, I estimate the following equation in which an interaction term of Indian firm size and the upstreamness measure is added to the previous specification:

$$ln\ E^c_{ipt} = \alpha_t + \alpha_p + \beta_1 ln\ S_{it} + \beta_2 ln\ S_{it} \cdot U_p + \varepsilon_{ipt} \tag{1.11}$$

where U_p is the Antras-Chor-Fally-Hillberry upstreamness measure described in the previous section. The direct impact of upstreamness U_p is absorbed by the product fixed effect α_p. The coefficient β_2 measures the change in the buyer-size elasticity as the distance from final use of the product traded varies. The first empirical prediction of the model in section 2 suggests that β_2 should be negative and significant. As the product traded is closer to final consumption (U_p is *decreasing*), the strength of assortative matching is stronger - the average size of the buyers with whom an Indian supplier interacts is increasing with Indian supplier size. The total elasticity of average buyer size with respect to Indian firm size for a given product with upstreamness U_p will be given by $\beta_1 + \beta_2 \cdot U_p$.

To test the second and third predictions of the theoretical model regarding the role the elasticity of demand faced by the US firm, I estimate the following equation:

$$\begin{aligned} ln\ E^c_{ipt} = {} & \alpha_t + \alpha_p + \beta_1 ln\ S_{it} + \beta_2 ln\ S_{it} \cdot U_p + \beta_3 ln\ S_{it} \cdot B_{ipt} + \beta_4 ln\ S_{it} \cdot B_{ipt} \cdot U_p + \\ & + \beta_5 U_p \cdot B_{ipt} + \beta_6 B_{ipt} + \varepsilon_{ipt} \end{aligned} \tag{1.12}$$

where B_{ipt} is the buyer demand elasticity faced by Indian exporter i in product p at time t, and it is calculated as a weighted average of the the demand elasticities with whom the Indian exporter interacts in product p at time t. Note that because the buyer demand elasticity varies at the Indian firm-product level, is not absorbed by the product fixed effect. The model predicts that $\beta_3 + \beta_4$ will be positive and significant. The strength of positive assortative matching is stronger when the US buying firm faces a very elastic demand at all stages of production. The third prediction of the theoretical mode is that β_4 will be negative and significant. The strength of assortative matching will increase faster with downstreamness when the buyer sells a less differentiated product in the US market. In the estimation, B_{ipt} will be an indicator variable for whether the weighted average elasticity calculated at the Indian firm i, product p, year t is above the median elasticity.

Estimation Results

Table 1.2 panel A presents the results from estimating equation (4.1). In column (1) the dependent variable is the Indian exporter exposure to US firm size as measured by total employment. The results in column (1) which are the linear regression counterpart of the binned scatter plot in Figure 1.2, suggest that on average there is positive assortative matching in the sample. A doubling of Indian supplier size is associated with close to 24% increase in the average size of the buying firms with whom the supplier interacts. In column (2) the dependent variable is the Indian exporter exposure to US firm size as measured by the total value of imports. The results suggest that large Indian firms trade not only with large US firms, but also with large US importers. However, the magnitude of the elasticity is smaller. There is no association between Indian firm size and US buyer size as measured by the number of foreign suppliers a firm has. Lastly, large Indian firms are also more likely to be exposed to import-intensive US firms.

The results of estimating equation (1.11) are presented in table 1.2 panel B, and show that there is substantial heterogeneity in the estimated elasticity with the distance to final use of the product traded. The results confirm the first model prediction - the strength of positive assortative matching is increasing with the downstreamness of the product traded. The coefficient β_2 on the interaction of Indian firm size with the upstreamness measure is negative and statistically significant for all exposure variables. Column (1) reports the estimates of the elasticity of average US firm size as measured by employment with respect to Indian firm size along the value chain. The elasticity declines as the product traded is further away from final consumption suggesting the degree of assortative matching is strongest for consumer products and much weaker for products which primarily serve as intermediate inputs for other intermediate products. When the upstreamness measure is equal to 1, which is the case for most consumer products, the magnitude of the elasticity is firmly positive around 0.5. When upstreamness measure is approximately 3, the buyer size elasticity becomes zero. This implies that there is no statistically significant difference in the average size of buying firms for large and small Indian firms selling very upstream products. The elasticity becomes negative for products with upstreamness above 3, but the magnitude is very small.

Columns (2) and (3) show that the effect of upstreamness is robust to using other measures for US firm size constructed from the customs data. Larger Indian firms are likely to interact with larger importing firms, as measured by the value of total imports and the number of foreign suppliers, when they export products close to final consumption, but in very upstream product markets Indian firm size is not correlated with the average size of the importing partner. These results support the model intuition that the benefit to high-capability buyers of having high-capability suppliers is larger when suppliers enter the production line in later stages, and as a result they engage more in search in these later stages. The results in column (4) show that large Indian exporters increasingly engage in trade with import-intensive US firms as the product they export is further away from final use. When combined with the results in column (1), the results in column (4) suggest that the trading partners of large exporters for upstream products are likely to be specialized importers who trade very large volumes, but employ few employees in the US.

The results of testing the last two predictions of the model regarding the demand

Table 1.2: *Size Elasticities Along the Value Chain*

	Exposure to US Firm Characteristic			
	Size (ln employment) (1)	Import Size (ln Total Value Imported) (2)	Number of Suppliers (ln) (3)	Import Intensity (4)
	Panel A			
Indian Firm Size (ln Sales)	0.234***	0.129**	0.0459	0.100***
	(0.086)	(0.064)	(0.045)	(0.035)
Product Fixed Effects (HS4)	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
R-squared	0.252	0.316	0.328	0.239
	Panel B			
Indian Firm Size (ln Sales)	0.708***	0.253***	0.245***	-0.0712
	(0.174)	(0.094)	(0.073)	(0.063)
Indian Firm Size x Upstreamness	-0.220***	-0.0576*	-0.0925***	0.0797***
	(0.062)	(0.032)	(0.025)	(0.024)
Product Fixed Effects (HS-4)	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
R-squared	0.258	0.316	0.331	0.242

Notes: The unit of observation is an Indian firm *i,* exporting product *p* at time *t*. The dependent variables in columns (1) to (4) is the Indian firm exposure to a US firm characteristic in product *p* in year *t*. The exposure to a US firm characteristic is calculated as the weighted average of the US firm characteristic with whom an Indian firm trades in product *p* at time *t,* with weights equal to the share of exports to the US firm. In column (1), the dependent variable is the natural logarithm of exposure to US firm employment. In column (2), the US firm characteristic used is the total value of imports, in column (3), the characteristic used is the total number of suppliers, and in column (4), the characteristic used is the total value of imports divided by total employment. All regressions include product fixed effects (at the HS 4-digit classification) and year fixed effects. Product upstreamness which measures the average distance from final use of a given product. The upstreamness measure varies from 1 to 4.65. Standard errors in parentheses are clustered at the Indian firm level. The sample is composed of 1050 Indian firms, 700 products over 12 years (1995 to 2007). *** p<0.01, ** p<0.05, *p<0.1

elasticity faced by the buyer are presented in Table 1.3, and are broadly in line with the predictions of the model. The first two columns present the results of estimating 1.10 by splitting the sample of Indian firms by the median elasticity, which is calculated at the Indian firm, product, year level. The "high buyer-demand elasticity" subsample contains those Indian firm-product-year observations for which the average buyer-demand elasticity is above the median. The magnitude of the elasticity is 0.4 when Indian firms trade with US firms facing a very elastic demand (on average) and 0.3 when they trade with US firms selling a less elastic demand. This suggests that on average (at all stages of production) larger Indian firms are more likely to trade with larger US firms when the US firms they interact with face a very elastic demand. However, the differences in average elasticities in the two subsamples are not statistically significant, as suggested by column (3) which presents the results of estimating 1.10 and adding the interaction of Indian firm size with an indicator variable for whether the average elasticity of the buyers to whom an Indian firm i is selling product p is above the median. This interaction term is positive, but not statistically significant, suggesting that on average the buyer-size demand elasticities for firms trading with buyers facing high and low demand elasticities are equal, on average. Columns (4) to (6) reveal that the buyer-size elasticities are higher for Indian firms trading with buyers facing a very elastic demand only in later stages of production (product upstreamness is above 2) offering partial support for the second empirical prediction of the theoretical model. For very upstream products, the elasticity is negative for high buyer-demand elasticity and close to zero for low buyer-demand elasticity. The third prediction of the model which states that the buyer-size elasticity increases more rapidly with the stage of production when buyers face a very elastic demand finds support in the data. In column (6), the coefficient β_4 from estimating equation 1.12 is negative and statistically significant. While the third prediction of the theoretical model is not in line with the empirical results for the upper range of the upstreamness variable, a potential problem is that the averaging of the buyer elasticities at the Indian firm, product, year level will hide heterogeneity in the relationships between buyers and suppliers and the elasticity of demand faced by the buyers. The second

Table 1.3: *Size Elasticities Along the Value Chain: The Role of Demand Elasticity*

	Average US Firm Size (ln employment)					
	High Buyer Demand Elasiticity	Low Buyer Demand Elasiticity	Full Sample	High Buyer Demand Elasiticity	Low Buyer Demand Elasiticity	Full Sample
	(1)	(2)	(3)	(4)	(5)	(6)
Indian Firm Size (ln Sales)	0.401***	0.317***	0.318***	0.949***	0.597***	0.626***
	(0.073)	(0.070)	(0.072)	(0.169)	(0.152)	(0.152)
Indian Firm Size x High Buyer Demand Elasticity (=1)			0.048			0.302**
			(0.062)			(0.126)
Indian Firm Size x Upstreamness				-0.264***	-0.127**	-0.139**
				(0.071)	(0.058)	(0.058)
Indian Firm Size x High Buyer Demand Elasticity (=1) x Upstreamness						-0.128**
						(0.057)
HS-4 Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Clustering Indian Firm	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.358	0.345	0.297	0.354	0.362	0.304

Notes: The unit of observation is an Indian firm i, exporting product p at time t. The dependent variable is the average US firm employment with whom an Indian firm trades in product p at time t. All regressions include product fixed effects (defined at the HS 4-digit classification) and year fixed effects. Product upstreamness measures the average distance from final use of a given product. The upstreamness measure varies from 1 to 4.65. The buyer demand elasticity is calculated using Broda-Weinstein elasticities of import demand and expressed at the HS-10 or NAICS 6-digit level. The subsamples high/low buyer demand elasticities are obtained by splitting the sample by the median elasitcity calculated at the Indian firm, product, time level. Standard errors in parentheses are clustered at the Indian firm level. The full sample is composed of 1050 Indian firms, 700 products over 12 years (1995 to 2007). *** p<0.01, ** p<0.05, *p<0.1

empirical strategy presented in the next section will address this issue.

Alternative Hypotheses

There are a number of potential alternative explanations for the observed correlation between the strength of the assortative matching patterns and product upstreamness. Product upstreamness may be spuriously correlated with other product measures that are relevant for the matching of buyers and suppliers in international trade. I derive these hypotheses based on existing theories in international trade and the empirical correlations of the upstreamness measure with other product characteristics presented in table 1.4.

The first alternative explanation for the observed patterns is that the matching process is driven by product specificity, and not by the distance to final use of the product traded. In particular, a concern here is that upstream products are more likely to be commodity-like products which have a reference price or are sold on an organized exchange. When the

Table 1.4: *The Relationship Between Product Upstreamness and Other Product Characteristics*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Rauch Measure	*Broda-Weinstein Elasticity*	*Price-Revenue Elasticity*	*Advertising Intensity*	*R&D Intensity*	*Capital intensity*	*Ratio Sellers/Buyers (HS-10)*	*Price dispersion (HS-10)*
Upstreamness	0.256**	-0.0681+	-0.127**	-0.00633**	0.00438**	2.273**	-0.414**	0.742**
	(0.018)	(0.040)	(0.009)	(0.000)	(0.001)	(0.120)	(0.046)	(0.070)
Constant	-0.261**	1.974**	0.221**	0.0268**	0.00824**	-0.776**	3.509**	0.152
	(0.043)	(0.096)	(0.021)	(0.001)	(0.002)	(0.293)	(0.111)	(0.169)
R-squared	0.232	0.004	0.243	0.245	0.035	0.339	0.106	0.14

Notes: Standard errors in parentheses. ** p<0.01, * p<0.05, + p<0.1

product traded is a commodity, a high-capability supplier may be easily substitutable with a lower-capability supplier. I use the Rauch (1999) measure which classifies products based on whether they are sold on an organized exchange, have a reference price or neither and the Broda and Weinstein (2006) estimates of import demand elasticities for the product traded to to test the robustness of my results to this alternative explanation. Table 1.5 presents the results from estimation equation (2) including controls for Indian firm size interaction with the Rauch product measure (panel A) and the the Broda and Weinstein (2006) import demand elasticity of the product trade (panel B). The results show that β_2 remains significant and the magnitude remains almost unchanged. The matching process is not seem to be driven by the correlation between upstreamness and product specificity.

The second alternative explanation is that the assortative matching between buyers and suppliers is based on "quality" - buyers whose products have high-quality work with suppliers who are able to deliver high-quality inputs - and upstreamness captures the scope for quality differentiation of a given product. An extensive literature in international trade has examined the implications of quality differentiation for firm's pricing decisions and export performance. To capture a product's scope for quality differentiation, I employ two measures which exhibit the highest correlation with upstreamness among the set of measures previously used in the literature to capture scope for quality differentiation [10] the

[10] The results are robust for controlling for other "quality" measures such as R&D intensity and the length of quality ladders measure developed by Khandelwal (2010).

advertising intensity and the price elasticity of revenue of the product traded. Advertising intensity is strongly negatively correlated with upstreamness, which is intuitive since the industries that are most advertising intensive are closest to final consumers. The price elasticity of revenue is a measure I construct from value and quantity data in the US import customs transactions. In particular, within each HS 4-digit product in a given year, I regress the log of unit values on the log of export revenues at the exporting firm level[11]. A positive price elasticity of revenue suggests that exporting firms exporting those products earn higher revenues by setting higher prices on average, consistent with an environment where there is scope for quality differentiation. Products with a negative elasticity are likely to exhibit low scope for quality differentiation since on average higher revenues are associated with lower prices. The price elasticity of revenue measure is negatively correlated with upstreamness suggesting that upstream products are more likely to be "cost" industries with low scope for quality differentiation, while more downstream products have higher scope for quality differentiation. Table 1.6 shows that the sorting of buyers and suppliers along the production chain is robust to including interactions with the product measures that captures the scope for quality differentiation. As previously, the coefficient β_2 remains significant and the magnitude remains roughly unchanged.

Finally, I control for two other product characteristics that are correlated with upstreamness, namely capital intensity of the product traded and the ratio of the number of sellers to the number of buyers who are active trading a given product. Capital intensity exhibits a highest correlation with product upstreamness, suggesting that consumer products are on average more labor intensive than upstream products. The ratio of buyers and sellers captures the (relative) market of thickness in a given product is negatively correlated with upstreamness. Downstream products have more sellers per buyer on average relative to upstream products. The results in table 1.7 show that the sorting patterns along the value chain are also robust to controlling for these product characteristics.

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[11] Manova and Zhang (2012) employ the same type of regression in exploring the export prices of Chinese exporters.

Table 1.5: *Size Elasticities Along the Value Chain Controlling for Product Specificity*

	Exposure to US Firm Characteristic			
	Size (ln employment) (1)	Import Size (ln Total Value Imported) (2)	Number of Suppliers (ln) (3)	Import Intensity (4)
		Panel A		
Indian Firm Size (ln Sales)	0.726***	0.328***	0.256***	-0.0985*
	(0.167)	(0.085)	(0.068)	(0.058)
Indian Firm Size x Upstreamness	-0.235***	-0.118**	-0.102***	0.102***
	(0.068)	(0.047)	(0.033)	(0.028)
Indian Firm Size x Rauch Measure	0.0554	0.224**	0.0334	-0.0808
	(0.136)	(0.113)	(0.076)	(0.071)
Product Fixed Effects (HS-4)	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
R-squared	0.258	0.318	0.331	0.242
		Panel B		
Indian Firm Size (ln Sales)	0.475***	0.0726	0.141*	0.0169
	(0.164)	(0.128)	(0.082)	(0.090)
Indian Firm Size x Upstreamness	-0.213***	-0.0521*	-0.0893***	0.0770***
	(0.060)	(0.031)	(0.024)	(0.023)
Indian Firm Size x Broda-Weinstein Elasticity	0.111**	0.0856**	0.0494**	-0.0419
	(0.049)	(0.036)	(0.023)	(0.027)
Product Fixed Effects (HS-4)	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
R-squared	0.259	0.318	0.332	0.242

Notes: The unit of observation is an Indian firm *i*, exporting product *p* at time *t*. The dependent variables in columns (1) to (4) is the Indian firm exposure to a US firm characteristic in product *p* in year *t.* The exposure to a US firm characteristic is calculated as the weighted average of the US firm characteristic with whom an Indian firm trades in product p at time t, with weights equal to the share of exports to the US firm. In column (1), the dependent variable is the natural logarithm of exposure to US firm employment. In column (2), the US firm characteristic used is the total value of imports, in column (3), the characteristic used is the total number of suppliers, and in column (4), the characteristic used is the total value of imports divided by total employment. All regressions include product fixed effects (at the HS 4-digit classification) and year fixed effects. Product upstreamness which measures the average distance from final use of a given product. The upstreamness measure varies from 1 to 4.65. The Rauch Measure equals 1 if the product is sold in an organized exchange or has a reference price. The Broda-Weinstein elasticity measures the median import demand elasticity for the HS 4-digit sector. Standard errors in parentheses are clustered at the Indian firm level. The sample is composed of 1050 Indian firms, 700 products over 12 years (1995 to 2007). *** p<0.01, ** p<0.05, *p<0.1.

Table 1.6: *Size Elasticities Along the Value Chain Controlling for Product Scope for Quality Differentiation*

	Exposure to US Firm Characteristic			
	Size (ln employment) (1)	Import Size (ln Total Value Imported) (2)	Number of Suppliers (ln) (3)	Import Intensity (4)
	Panel A			
Indian Firm Size (ln Sales)	0.795***	0.221**	0.285***	-0.11
	(0.217)	(0.106)	(0.084)	(0.077)
Indian Firm Size x Upstreamness	-0.238***	-0.0513	-0.101***	0.0875***
	(0.070)	(0.035)	(0.028)	(0.025)
Indian Firm Size x Advertising Intensity	-3.533	1.264	-1.639	1.561
	(3.594)	(2.183)	(1.778)	(2.116)
Product Fixed Effects (HS-4)	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
R-squared	0.258	0.316	0.331	0.242
	Panel B			
Indian Firm Size (ln Sales)	0.752***	0.298***	0.237***	-0.112*
	(0.178)	(0.093)	(0.074)	(0.064)
Indian Firm Size x Upstreamness	-0.252***	-0.0902**	-0.0872***	0.109***
	(0.069)	(0.037)	(0.029)	(0.027)
Indian Firm Size x Price-Revenue Elasticity	-0.314	-0.326**	0.0529	0.292**
	(0.233)	(0.154)	(0.141)	(0.118)
Product Fixed Effects (HS-4)	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
R-squared	0.258	0.317	0.331	0.243

Notes: The unit of observation is an Indian firm *i*, exporting product *p* at time *t*. The dependent variables in columns (1) to (4) is the Indian firm exposure to a US firm characteristic in product *p* in year *t*. The exposure to a US firm characteristic is calculated as the weighted average of the US firm characteristic with whom an Indian firm trades in product *p* at time *t*, with weights equal to the share of exports to the US firm. In column (1), the dependent variable is the natural logarithm of exposure to US firm employment. In column (2), the US firm characteristic used is the total value of imports, in column (3), the characteristic used is the total number of suppliers, and in column (4), the characteristic used is the total value of imports divided by total employment. All regressions include product fixed effects (at the HS 4-digit classification) and year fixed effects. Product upstreamness which measures the average distance from final use of a given product. The upstreamness measure varies from 1 to 4.65. Advertising intensity measures the spending on advertisiting services as a share of total spending on inputs in a given industry. The price-revenue elasticity measures the average elasticity of unit values with respect to revenues at the HS 4-digit level in the US import data. Standard errors in parentheses are clustered at the Indian firm level. The sample is composed of 1050 Indian firms, 700 products over 12 years (1995 to 2007). *** p<0.01, ** p<0.05, *p<0.1.

Table 1.7: *Size Elasticities Along the Value Chain Controlling for Product Capital Intensity and Market Thickness*

	Exposure to US Firm Characteristic			
	Size (ln employment) (1)	Import Size (ln Total Value Imported) (2)	Number of Suppliers (ln) (3)	Import Intensity (4)
	Panel A			
Indian Firm Size (ln Sales)	0.704***	0.250***	0.244***	-0.07
	(0.175)	(0.096)	(0.074)	(0.064)
Indian Firm Size x Upstreamness	-0.279***	-0.101**	-0.101***	0.0975***
	(0.074)	(0.046)	(0.034)	(0.035)
Indian Firm Size x Capital Intensity	0.115	0.0842	0.016	0.0163
	(0.099)	(0.068)	(0.052)	(0.052)
Product Fixed Effects (HS-4)	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
R-squared	0.259	0.317	0.331	0.242
	Panel B			
Indian Firm Size (ln Sales)	0.579***	0.240*	0.124	-0.03
	(0.168)	(0.127)	(0.086)	(0.096)
Indian Firm Size x Upstreamness	-0.204***	-0.0560*	-0.0771***	0.0745***
	(0.057)	(0.030)	(0.023)	(0.025)
Indian Firm Size x Ratio Sellers/Buyers	0.0282	0.00272	0.0265	-0.00905
	(0.036)	(0.024)	(0.019)	(0.016)
Product Fixed Effects (HS-4)	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
R-squared	0.258	0.316	0.331	0.242

Notes: The unit of observation is an Indian firm *i*, exporting product *p* at time *t*. The dependent variables in columns (1) to (4) is the Indian firm exposure to a US firm characteristic in product *p* in year *t.* The exposure to a US firm characteristic is calculated as the weighted average of the US firm characteristic with whom an Indian firm trades in product *p* at time *t,* with weights equal to the share of exports to the US firm. In column (1), the dependent variable is the natural logarithm of exposure to US firm employment. In column (2), the US firm characteristic used is the total value of imports, in column (3), the characteristic used is the total number of suppliers, and in column (4), the characteristic used is the total value of imports divided by total employment. All regressions include product fixed effects (at the HS 4-digit classification) and year fixed effects. Product upstreamness which measures the average distance from final use of a given HS 4-digit product. The upstreamness measure varies from 1 to 4.65. The capital intensity measures the ratio of total capital stock to employment at the HS 4-digit level . The ratio of buyers to sellers is measured using the number of exporters to the US and the number of US firms active trading a given HS 4-digit product in the US import data. Standard errors in parentheses are clustered at the Indian firm level. The sample is composed of 1050 Indian firms, 700 products over 12 years (1995 to 2007). *** p<0.01, ** p<0.05, *p<0.1.

1.4.2 Estimating the Probability of Positive Trade Between Firms

While the buyer size elasticities are informative for the underlying correlations in the data, a shortcoming of this empirical strategy is that it does not allow us to fully take advantage of the information on heterogeneity in relationships between Indian and US firms. Moreover, the OLS regressions described in the previous section do not allows us to control easily for other US firm characteristics that may be correlated with US firm size and may be the driver of matching, such as US firm age and types of activity. Existing studies documenting the heterogeneity of US importers using the LFTTD database have emphasized the *type and number of economic activities firms* performed by US firms as an important source of heterogeneity (Bernard et al., 2010). To the extent that firm activities are correlated with US firm size, and the true matching process with Indian firms is based on firm activity rather than firm size, the positive relationship between the likelihood of observing trade between the US and Indian firm size will be spurious.

I employ an alternative empirical strategy to establish assortative matching between Indian suppliers and US buyers, which allows me to address these concerns. I estimate a linear probability model of the probability that a US importer and an Indian exporter engage in a trading relationship as a function of importer and exporter size. The specification of this equation is tightly related to the theoretical model in that trade between exporter i and importer m is greater than zero if the benefits of establishing the match at stage i, $r'(i)$ are greater than the matching costs $c(p)$.

To be able to estimate the model, the original dataset needs to be modified to account for those relationships between buyers and suppliers in the sample that *were not realized*, i.e trade "zeros". To create the trade "zeros" within a given product, I construct the set of importers M who are active in buying product p (at the HS 4-digit level) in year t in the matched sample. The set M is restricted to include the US importers in the matched sample[12]. This entails creating all possible matches between importers and exporters

[12]Note that set M can be defined as all the importers buying product p from India at time t. This would include the set of importers in the matched sample and the importers who are buying product p from Indian

The initial matched sample of Indian and US firms contains all the observations with positive trade between US firms and their Indian suppliers. In each product p at year t, I create an indicator variable I_{impt} which is equal to 1 if a trading relationship between exporter i and importer m exists in the matched dataset, and zero if the trading relationship does not exist. The unit of observation is an Indian supplier (i), US buying firm (m), product p, in year t.

The estimation equation is given by

$$I_{impt} = \lambda_p + \lambda_t + \beta_1 ln\ S_{it} + \beta_2 ln\ Emp_{mt} + \beta_3 ln\ S_{it} \cdot ln\ Emp_{mt} + X_{mt}\Gamma + \varepsilon_{impt} \tag{1.13}$$

I_{impt} is the indicator which equals 1 if a trading relationship exists between exporter i and importer m in product p in year t in the matched sample. λ_p are product (HS 4-digit) fixed effects and λ_t are year (1995-2007) fixed effects. S_{it} is the size (total revenues) of the exporter i at time t and Emp_{mt} is the size of the importer m (total employment) active in trading product p at time $t.X_{mt}$ is a vector of time varying importer characteristics, such as age and type of activity and their interactions with Indian firm size.

In this equation, the likelihood of observing trade between an exporter i and an importer m in a given product p at time t is explained by the coefficient β_3 on the interaction term between Indian firm size and US firm size. A positive and significant β_3 implies there will be positive assortative matching of size between US firms and their Indian suppliers. The interaction term between US firm size and Indian firm size is intuitive in the light of a super-modular production function in which the cross-partial derivative of the joint payoff function with respect to the performance of the buyer and the supplier is positive.

To test the first prediction of the theoretical model regarding the strength of assortative matching along the value chain, I estimate the following equation:

firms that are not in the original sample

$$I_{impt} = \lambda_p + \lambda_t + \beta_1 ln\ Size_{it} + \beta_2 ln\ Emp_{mt} + \beta_3 ln\ S_{it} \cdot ln\ Emp_{mt} +$$
$$+\beta_4 ln\ S_{it} \cdot ln\ Emp_{mt} \cdot U_p + \beta_5 ln\ S_{it} \cdot U_p + \beta_6 ln\ Emp_{mt} \cdot U_p + X_{mt}\Theta + \varepsilon_{impt} \quad (1.14)$$

As in the previous empirical specification, U_p is the product upstreamness measure developed by Antràs et al. (2012). The vector X_{mt} contains US firm characteristics such as age and type of activity and their interactions double and triple interactions with Indian firm size and product upstreamness. The coefficient β_4 captures the effect of varying product upstreamness on the likelihood that larger Indian firms engage in trade with larger US firms. The first prediction of the model implies that β_4 should be negative and significant. The likelihood that larger Indian firms trade with larger US firms declines as the product traded is further away from final consumption, or, in the terminology of the model, increases as proximity to final consumption increases.

Testing the second and third predictions of the model regarding the demand elasticity faced by the US buying firms entails modifying the empirical specification in (1.14) by adding the demand elasticity faced by US firm which is calculated at the NAICS 6-digit level. The estimating equation is given by:

$$I_{impjt} = \lambda_p + \lambda_j + \lambda_t + \beta_1 ln\ Size_{it} + \beta_2 ln\ Emp_{mt} + \beta_3 ln\ S_{it} \cdot ln\ Emp_{mt} + \beta_4 ln\ S_{it} \cdot ln\ Emp_{mt} \cdot U_p +$$
$$+\beta_5 ln\ S_{it} \cdot ln\ Emp_{mt} \cdot B_j + \beta_6 ln\ S_{it} \cdot ln\ Emp_{mt} \cdot B_j \cdot U_p + X_{mt}\Theta + X_{it}\Gamma + \varepsilon_{impjt}$$
$$(1.15)$$

I_{impjt} is an indicator variable which equals 1 if positive trade exists in in product p at time t between Indian firm i and US importing firm m with industry classification j. λ_p is a product traded fixed effect (HS-4), λ_j is the buyer's industry fixed effect (NAICS 6-digit).B_j is an indicator for whether the elasticity of demand faced by the US importing firm is above the median elasticity in the sample. X_{mt} and X_{it} are vectors of time-varying importer and exporter characteristics and their interactions with product and industry characteristics.

The second prediction of the model suggests that $\beta_5 + \beta_6$ is positive and significant. This means that the likelihood that larger Indian firms trade with larger US firms is higher if the US buyer faces a very elastic demand, at all stages of production. The third prediction of the model regarding the interaction of product upstreamness and the buyer demand elasticity is that as we move down the production chain towards final consumption the probability that larger Indian firms trade with larger US firms increases more rapidly with the elasticity of demand faced by the US buyer. This implies that β_6 is negative and significant.

Estimation Results

The results of estimating equation (1.13) are presented in Table 1.8 in columns (1) to (4). Columns (1) and (2) do not contain any controls for US and Indian firm characteristics. In Column (1) we control for product fixed effects at the HS 4-digit level, while in columns (2) -(4) the fixed effects are at the US importer industry (NAICS 6-digit), product (HS 4-digit), Indian industry (ISIC 2-digit). In column (3), I control for US and Indian firm age and their interactions with Indian and US firm size respectively, as well as their interaction. I column (4), I include controls for the types of activity US firms engage in and their interactions with Indian firm size. Specifically, I control for manufacturing, retail, wholesale intensity, and headquarter intensity of US firms.

The results show that the coefficient on the interaction term between Indian and US firm size in equation (4.4) is positive and significant, consistent with positive assortative matching on firm size between Indian and US firms. These results are robust to using US and Indian firm industry fixed effects, controlling for firm age, and the types of activities carried out by US firms. Note that the magnitude of the interaction term (shown in column (3)) declines when controls for the types of activity of US firms and their interactions with Indian firm size are included in the regression. The interaction terms (not presented in this table) show that this is due to the inclusion of headquarter and retail intensity variables (the share of US firm employment engaged in management and administration activities, and retail activities respectively) which are positively correlated with US firm size. The headquarter and retail intensity interactions with Indian firm size are positive and significant. To the extent that headquarter intensity also proxies for US firm capability, these results support the predictions of the model. The results for the buyer retail intensity are also in line with the intuition of the model - the marginal benefit of search for high-capability suppliers is higher when buyers and supplier meet in later stages of production, where buyers are more likely to be engaged in retail.

In terms of magnitude, the estimated coefficient in column (2) suggests that a one standard deviation joint increase in logarithm of Indian firm size (1.6) and US firm size (2.92) increases the likelihood of observing trade between the firms by 0.015, which is 5 percent of the mean probability of trading. Indian firms whose size is one standard deviation above the mean are 20 percent more likely to engage in trade with US firms whose size is one standard deviation above the mean relative to US firms with one standard deviation below the mean.

Columns (5) to (8) of Table 1.8 present the results from estimating equation (1.14) in which the size interaction term and added controls are further interacted with product upstreamness. In all specifications, the coefficient β_4 is negative, supporting the first prediction of the theoretical model, namely that the strength of positive assortative matching is increasing with the stage of production. The estimated effect of the firm size interaction term and its triple interaction with product upstreamness continues to be significant and remains approximately the same in magnitude when US firm covariates are added to the regression. Note the magnitude of the $\beta_3 + \beta_4$ coefficient on the firm size interaction term varies from approximately 0.005 when the product traded is close to final consumption (the value of product upstreamness is 1) to 0 for products with upstreamness around 3. The upstreamness cut-off when the sign of assortative matching becomes negative is approximately equal to the cut-off obtained using the previous empirical specification. The triple interaction term is negative for very upstream products, suggesting that larger Indian firms are more likely to trade with smaller US firms in that region of the product space. In terms of magnitude, a one standard deviation joint increase in logarithm of Indian firm size

(1.6) and US firm size (2.92) increases the likelihood of observing trade between the firms by 0.047 (18 percent of the mean probability of observing positive trade in the sample), when Indian firms export consumer products to US firms. Similarly, Indian firms whose size is one standard deviation above the mean are 50 percent more likely to engage in trade with US firms whose size is one standard deviation above the mean relative to US firms with one standard deviation below the mean. The likelihood of engaging in trade with large US firms does not vary with Indian firm size when the parties trade very upstream product.

To test the last two predictions of the model regarding the strength of assortative matching and the elasticity of demand faced by the US firms, I first split the sample by the median buyer demand elasticity and re-estimate equations (1.13) and (1.14) in the two subsamples. I then estimate equation (1.15) using the full sample. The results from estimation equations (1.13) and (1.14) are presented in panels B and C of Table 1.8. Columns (1) to (4) in panels B and C show the magnitude of the coefficient β_3 on the Indian and US firm size interaction is almost three times as large when the sample is restricted to US firms facing an elasticity of demand above median. These results support the third prediction of the theoretical model which states that the likelihood of larger Indian firms engaging in trade with larger US firms is higher when the US buyer faces a very elastic demand. The revenue generated at a given stage of production is more sensitive to supplier's capability, and as a result the high-capability buyers are more likely to engage in search for high-capability suppliers, generating stronger positive assortative matching. Columns (5) to (8) present the results of estimating equation (1.14) in the two subsamples. The coefficient β_4 on the triple interaction term of US and Indian firm size and product upstreamness is larger in magnitude and only statistically significant when the sample is restricted to those buyers facing high elasticity of demand. These results are consistent with the fourth prediction of the theoretical model which states that the elasticity of demand faced by the buyer magnifies the impact of downstreamness on the investments in supplier search and implies that the strength of assortative matching increases faster with the stage of production when the buyer faces a very elastic demand.

Table 1.9 summarizes the results obtained from splitting the sample by the median buyer demand elasticity as well as presents the results from estimating equation (1.15) in column (6). The results in column (3) suggests that the magnitude of the size interaction coefficients obtained from the two subsamples are statistically different. The magnitude of the size interaction term is almost three times as large when US buyers operate in industries where the elasticity of demand is high. The results in column (6) broadly support the predictions of the model. In particular β_6 is negative and significant suggesting that the likelihood of larger buyers and suppliers engaging in trade increases more rapidly with the stage of production when the elasticity of demand faced by US buyers is high. When Indian firms export consumer products (the product upstreamness measure has a value of 1), the coefficients on the size interaction term are 0.006 and 0.002 for high and low buyer demand elasticities, respectively. The magnitude of the size interaction coefficient becomes zero for both high and low demand elasticity when the product traded has upstreamness around 3, and becomes negative for upstreamness values above 3. For these products, the magnitude of the size interaction coefficient is higher (less negative) when the US buyer faces a less elastic demand. However, the difference in the magnitudes of these elasticities is small. In sum, the results in tables 1.8 and 1.9 are broadly consistent with the prediction of the theoretical model regarding the strength of the assortative matching between buyers and suppliers, and the elasticity of demand faced by the buyer. Because buyer revenues are more sensitive to supplier's capability when the product variety sold by the US buyer in the final goods market has close substitutes, high-capability buyers will find it optimal to invest more resources in search for the high-capability suppliers, leading to stronger positive assortative matching.

Table 1.8: *US and Indian Firm Size and the Selection Into a Trading Relationship Along the Value Chain*

	Dependent Variable=Indicator for Trading Relationship Between a US Firm and an Indian Firm							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Panel A: All Observations				
US Firm Size (ln) x Indian Firm Size (ln)	0.00335***	0.00340***	0.00382***	0.00258***	0.00721***	0.00767***	0.00767***	0.00722***
	(0.00055)	(0.00050)	(0.00058)	(0.00052)	(0.00116)	(0.00120)	(0.00131)	(0.00109)
US Firm Size(ln) x Indian Firm Size (ln) x Upstreamness					-0.00206***	-0.00235***	-0.00210***	-0.00218***
					(0.00043)	(0.00045)	(0.00050)	(0.00042)
				Panel B: High Buyer Demand Elasticity				
US Firm Size (ln) x Indian Firm Size (ln)	0.00440***	0.00453***	0.00502***	0.00338***	0.00785***	0.00846***	0.00872***	0.00788***
	(0.00053)	(0.00056)	(0.00059)	(0.00063)	(0.00091)	(0.00092)	(0.00103)	(0.00089)
US Firm Size(ln) x Indian Firm Size (ln) x Upstreamness					-0.00216***	-0.00244***	-0.00232***	-0.00245***
					(0.00044)	(0.00044)	(0.00051)	(0.00044)
				Panel C: Low Buyer Demand Elasticity				
US Firm Size (ln) x Indian Firm Size (ln)	0.00168***	0.00148***	0.00185***	0.000943*	0.00369***	0.00329**	0.00280*	0.00325**
	(0.00044)	(0.00050)	(0.00053)	(0.00050)	(0.00138)	(0.00138)	(0.00146)	(0.00136)
US Firm Size(ln) x Indian Firm Size (ln) x Upstreamness					-0.000865	-0.000819	-0.000382	-0.00109*
					(0.00055)	(0.00056)	(0.00060)	(0.00057)
Controls								
US Industry x Product Traded x Indian Industry FE	N	Y	Y	Y	N	Y	Y	Y
Product Traded FE (HS-4-digit)	Y	N	N	N	Y	N	N	N
Year Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y
US Firm Age and Interactions	N	N	Y	Y	N	N	Y	Y
Indian Firm Age and Interactions	N	N	Y	Y	N	N	Y	Y
Activities intensity and Interactions	N	N	N	Y	N	N	N	Y
R-squared	0.255	0.255	0.256	0.255	0.256	0.256	0.257	0.256

Notes: The unit of observation is an Indian firm *i*, US firm *m* trading product *p* at time *t*. The dependent variable is an indicator variable which equals 1 if a trading relationship exists between the Indian firm *i* and US firm *m* in product *p* at time *t*, and zero otherwise. All columns contain controls for US firm size, Indian firm size, and their interactions with product upstreamness when appropriate. All columns except column (1) and (5) contain a US Industry (NAICS 6-digit -, product traded (HS 4-digit) - Indian firm industry (ISIC 2-digit) fixed effect. Columns (1) and (5) contain a product traded fixed effect. The upstreamness measure varies from 1 to 4.65. The buyer demand elasticity is calculated using Broda-Weinstein elasticities of import demand and expressed at the NAICS 6-digit level. The measure varies from 1 to 57, and it is expressed in natural log. Standard errors in parentheses are clustered at the product level level. The sample is composed of 1050 Indian firms, 4100 US firms, 700 products over 12 years (1995 to 2007). *** p<0.01, ** p<0.05, *p<0.1

Table 1.9: *US and Indian Firm Size and the Selection Into a Trading Relationship Along the Value Chain: The Role of Demand Elasticity*

	Dependent Variable=Indicator for Trading Relationship Between a US Firm and an Indian Firm					
	High Buyer Demand Elasticity	Low Buyer Demand Elasticity	All sample	High Buyer Demand Elasticity	Low Buyer Demand Elasticity	All sample
	(1)	(2)	(3)	(4)	(5)	(6)
US Firm Size (ln) x Indian Firm Size (ln)	0.00453***	0.00148***	0.00148***	0.00846***	0.00329**	0.00363***
	(0.00056)	(0.00050)	(0.00047)	(0.00092)	(0.00138)	(0.00132)
US Firm Size(ln) x Indian Firm Size (ln)				-0.00244***	-0.000819	-0.000995*
x Upstreamness				(0.00044)	(0.00056)	(0.00054)
US Firm Size (ln) x Indian Firm Size (ln)						0.00484***
x High Buyer Demand Elasticity (=1)			0.00298***			(0.00123)
			(0.00061)			
US Firm Size(ln) x Indian Firm Size (ln)						-0.00146**
x High Buyer Demand Elasticity (=1) x Upstreamness						(0.00066)
Controls						
US Industry x Product Traded x Indian Industry FE	Y	Y	Y	Y	Y	Y
Year Fixed Effects	Y	Y	Y	Y	Y	Y
R-squared	0.232	0.296	0.256	0.233	0.295	0.257

Notes: The unit of observation is an Indian firm i, US firm m trading product p at time t. The dependent variable is an indicator variable which equals 1 if a trading relationship exists between the Indian firm i and US firm m in product p at time t, and zero otherwise. All columns contain controls for US firm size, Indian firm size, and their interactions with product upstreamness when appropriate. All columns contain a US Industry (NAICS 6-digit -, product traded (HS 4-digit) - Indian firm industry (ISIC 2-digit) fixed effect. The upstreamness measure varies from 1 to 4.65. The buyer demand elasticity is calculated using Broda-Weinstein elasticities of import demand and expressed at the HS-10 digit or NAICS 6-digit level. The variable "High Buyer Demand Elasticity" equals 1 if the elasticity of demand faced by the US firm is above the median elasticity in the sample. Standard errors in parentheses are clustered at the product level level. The sample is composed of 1050 Indian firms, 4100 US firms, 700 products over 12 years (1995 to 2007). *** p<0.01, ** p<0.05, *p<0.1

1.5 Conclusion

Relationships between importing and exporting firms in global supply chains shape the interdependence of countries, but our understanding of how these firms match in international trade remains limited. Using a novel dataset that matches firm-level information on US importing firms with firm-level information on their Indian exporters, this paper explored theoretically and empirically the matching of trading firms at different stages in the global production chain. A theoretical model of sequential production featuring complementarities between the capability of buyers (US importers) and suppliers (Indian exporters) delivers three predictions regarding the strength of positive assortative matching along the value chain and the elasticity of final demand faced by the US importers. The model highlights that the incentives of high-capability buyers to invest in search for high-capability suppliers - and hence the strength of the positive assortative matching - are increasing with the stage of production, with the elasticity of demand faced by the buyer, and with the interaction of the stage of production and elasticity of demand. The model predictions find support in the matched data, and are robust to using different empirical strategies, and controlling for other product and firm characteristics. In particular, the results show that large Indian exporters are more likely to engage in trade with large US firms when the product traded is close to final use, as it is the case for consumer products. The positive matching patterns on firm size are also stronger when the US firms sells a less differentiated product in the US market, at all stages of the value chain. Finally, the strength of positive assortative matching also increases more rapidly with the stage of production when the US buyer faces a very elastic demand.

The results in this paper highlight the significant product and industry heterogeneity of sorting patterns between importing and exporting firms in the global economy, even within the same country pair. This suggests that average estimates of the strength of assortative matching in a pooled sample are likely to mask significant heterogeneity. The theoretical framework outlined in this paper highlights the trade-off between the marginal benefits of a superior match with a supplier and the frictions involved in generating that match.

Understanding more about the nature and magnitude of the costs of matching between firms and how they vary with importing firm and product characteristics is necessary to our understanding of trade costs. With the significant decline in tariffs and transportation costs over the last decades, the costs of establishing a match between importing and exporting firms might constitute the larger barrier to trade in today's global economy.

A next step in this research agenda is to explore the role of US importer heterogeneity for the productivity dynamics of Indian firms. An extensive literature in international trade has studied how exporting affects firm productivity, often using as motivation case study evidence on learning and technology transfer from developed country firms. The benefit of the matched dataset is that it allows us to disaggregate the firm export status to account for the heterogeneity of importers with whom exporters come into contact. The evidence presented in this paper has revealed that the matching patterns differ substantially across the value chain, and it may be fruitful to explore how firm productivity dynamics vary with buyer characteristics depending on the production line position of exporting firms. Neither the buyer heterogeneity that the matched data provides nor the importance of the position in the value chain of exporters have been explored by previous learning-by-exporting studies.

In its focus on firm-heterogeneity on both sides of the trade transaction, this paper contributes to the existing research agenda in international trade emphasizing the importance of firm heterogeneity for understanding trade patterns and the aggregate response of economies to trade policy shocks. That research has uncovered substantial heterogeneity in firm-level outcomes that vary with a firm's participation in international trade. Only a small fraction of firms engage in international trade, and those firms who do are larger and more productive than purely domestic firms. Within the group of trading firms, a small number of large firms account for most of trading activity in a given country. The research in this paper suggests that trade activity between countries may be very concentrated in a small number of (large) firm pairs when the product traded is close to final use. In future research, I will examine how these observed sorting patterns at the product level vary with the income-level exporting countries, and incorporate these features into the theoretical model. An understanding of how economies are linked through firm-to-firm relationships, might shed light on the transmission of shocks across countries, especially when explored through the lens of the "granularity" hypothesis in macroeconomics which emphasizes the importance of idiosyncratic shocks to (large) firms in generating aggregate fluctuations.

In that respect, the evidence presented in this paper on the heterogeneity in the matching of international buyers and suppliers - and the new matched data that allow us to observe this - may be an initial step towards understanding how that same firm-to-firm heterogeneity is relevant for understanding a broader range of economic phenomena.

Chapter 2

The Gender Effects of Exporting: Female Factory Work and Siblings' Education in Cambodia

2.1 Introduction

The shift in the geographic location of production from the developed to the developing world over the past decades has led to increased female labor force participation and the "feminization" of manufacturing employment in the developing world (World Bank, 2012). The expansion of low-skilled manufacturing exports (particularly apparel) has offered significant employment opportunities for young, unmarried women especially in Central America and Asia. This phenomenon has often been motivated with the preference for female workers in export factories due women's lower propensity to unionize, greater agility and tolerance for repetitive tasks, as well as lower wages relative to men (Standing (1999), Fontana (2009)). An extensive literature in economics has established that improving women's employment and income opportunities changes their bargaining power within the household and affects household decision-making (Strauss and Thomas (1995). Behrman (1997), Duflo (2003), Qian (2008)). While the extensive employment of women in export factories has received significant attention in the public domain, there has been little rigorous evaluation of the effects of this type of work on household outcomes. This paper estimates the impact of female export factory work on the school enrollment of siblings in the context of Cambodia. The focus on education as an outcome variable is motivated by extensive case study evidence which suggests that the education of younger sisters is an important recipient of the wages earned by older sisters working in apparel export factories[1].

As a result of increased market access to the United States, Cambodia has witnessed a remarkable growth in its apparel exports, from 4 million in 1996 to close to 4 billion in 2013. Apparel is by far the most important export industry in Cambodia, accounting for more than 80 percent of its exports. The expansion of the apparel industry resulted in a significant rise in job opportunities for women. Employment in export garment factories grew from 19,000 workers in 1996 to close to half a million in 2013 (Garment Manufacturers Association in Cambodia, 2013). More than 80 percent of workers are young women who migrate from rural areas to Phnom Penh, where the garment export cluster is located. The majority of female factory workers have never been married and still reside in their parents' households. In most cases, their wages represent the main source of income for their families. In 2006, the World Bank estimated that approximately 1.7 million people in Cambodia depend on the industry directly or indirectly (World Bank, 2006).

The main challenge in identifying the causal effect of female export factory work on the investments in education of siblings is selection bias – households who decide to send a daughter to work in the factory may be different from households who do not in ways that are unobserved to the econometrician and correlated with gender education decisions. To address the selection bias I use a household's proximity to garment factories as an instrument for its propensity to send a female migrant to work in the factory. I apply this instrument within the sample of households with at least one female member at "eligible" age to obtain a job in the factory, which is considered to be between 15 and 30[2]. The data

[1]See James (2014), Levi Strauss Foundation (2013), World Bank (2006)

[2]It has been argued that the preference for young women in export factories relates to their capacity to bear

used in the analysis comes from the 2004 round of Cambodia's Socio-Economic Household Survey. I focus on the sample of children below 15 years old, which is the minimum age of obtaining employment in the factory. The 2SLS estimates suggest that households who were induced to send a migrant daughter to work in the export factory are 40 percentage points more likely to be enrolled in school relative to their male siblings. The effects are larger and statistically significant only for the older cohort of siblings with ages between 10 and 15. We find that proximity to the factories does not affect young girls' relative propensity to attend school in households with no female household member at "eligible" age to obtain a job in the factory, in neither the 5-9 and 10-15 age cohorts. This provides support for the exogeneity assumption underlying the validity of the distance instrument.

The identification assumption underlying this estimation strategy is that any within-household differences in school enrollment of female siblings relative to their male siblings, between the households who reside in districts close to Phnom Penh relative to households in more distant districts, would have been the same in the absence of the expansion of the garment sector. To support this assumption, I show that the proximity to Phnom Penh is not associated with intra-household differences in young girls' relative propensity to enroll in school 1996, the year prior to Cambodia's normalization of trade relations with the United States, which was the catalyst of the garment export expansion.

The results are consistent with two channels, which are challenging to disentangle in the current setting. By increasing female-specific income garment jobs may increase older daughter's bargaining power within the household. If older female siblings have a higher preference for investing in their sisters relative to their older brothers, then this would lead to an increase the investment in education for girls. The second channel is that a member working in a job in an export factory raises total household income and this should increase investments in education for girls, if girls education is a luxury good relative to boys' education. The absence of any statistically significant reduced form effects of distance

children. Employers do not expect women to continue working in the factory once they establish their own families (Elson and Pearson, 1981).

on the propensity to attend schools in households with no "eligible" female member rules out two other explanations which are consistent with the results; that garments jobs may alter the relative return of investing girls' education and that women factory workers may act as role models for younger women and change their beliefs and aspirations, which in turn may affect their propensity to attend school.

I present suggestive evidence supportive of the first channel. The proximity to Phnom Penh is not associated with a higher propensity of female siblings to be enrolled in school relative to their male siblings in households with an older brother of eligible age to work in the factory, but with no daughter of eligible age. In addition, a simple test of girls' education being a luxury good for Cambodian households does not find support for this hypotheses. In the sample of households with no member employed in apparel, girls are not more likely to be enrolled in school relative to their brothers in richer households. However, in the absence of a shock of equal magnitude to male-specific income, these tests cannot completely rule out the income effect channel.

The quantitative results presented in this paper are consistent with qualitative evidence which suggests that garment workers direct some of their earnings towards the education of younger sisters. The extra income helps their sisters them stay in school in order to obtain higher-paying jobs outside the garment sector[3]. A descriptive analysis of the wage data suggests that the returns to schooling in the garment industry are non-existent, while they are positive in other paid jobs. Garment wages are on average twice as large relative to wages in the rest of the economy, but female wages in other sectors of the economy,such as education and other professional jobs, are higher than garment sector wages upon the completion of a high-school diploma. Moreover, garment jobs may incorporate compensating differentials for the occupational hazards and negative health impacts which may be associated with working in an export factory such as long hours, lack of ventilation and access to drinking water, inadequate lighting and use of strong chemicals[4].

[3]See World Bank (2006)

[4]A series of recent mass fainting in Cambodian export factories have bee associated with poor working

This paper contributes to two strands of literature. First, it makes a contribution to the study of the effects of trade, in particular exports, on educational investments in developing countries. Heath and Mobarak (2014) study the impact of the explosion of the garments industry in Bangladesh on educational investments in girls. They find that 5-10 year old girls are more likely to be enrolled in school relative to their male siblings. The authors interpret these results through garment jobs raising the returns to basic education, which is necessary to obtain a job in the factory. The authors find no differential effect on households where a female member is employed in the garments industry. We find that the gains in girls' schooling are concentrated in the 10 to 15 age cohort in household with a female member at the eligible age to obtain a job in the factory. This evidence rules the channel through which the arrival of export jobs raises the return to educating girls because factory work require basic education. This suggests that the apparel export jobs may have different skill requirements in different countries, and this may have different implications for the returns to educating girls in those countries. In the case of Mexico, Atkin (2012) finds that school dropout increased in municipalities on which there was expansion of export manufacturing opportunities, as the arrival of low-skilled manufacturing jobs raised the opportunity cost of schooling. The second strand of literature to which this paper is related is the literature on intra-household bargaining which finds that employment and income opportunities for women affect household decision making by changing the bargaining power within he household (Strauss and Thomas (1995). Behrman (1997)). This is explained by the fact that women have a relatively stronger preference for child's goods than men do. Additionally Duflo (2003) and Qian (2008) present evidence which suggests that that women have a stronger preference for expenditure on female children. The evidence presented in this paper is consistent with this latter mechanism.

The paper proceeds as follows: In section 2.2 I describe the rise of the Cambodian garment industry and the characteristics of women and work in the garment export factories. I continue with presenting the identification challenges and empirical strategy in section

conditions and inadequate nutrition (Thul, 2011).

2.3. Section 2.4 discusses the estimation results and possible mechanisms. In section 2.5, I present a robustness check for the identification assumption. Section 2.6 concludes.

2.2 The Garment Industry in Cambodia and Its Effects on Women

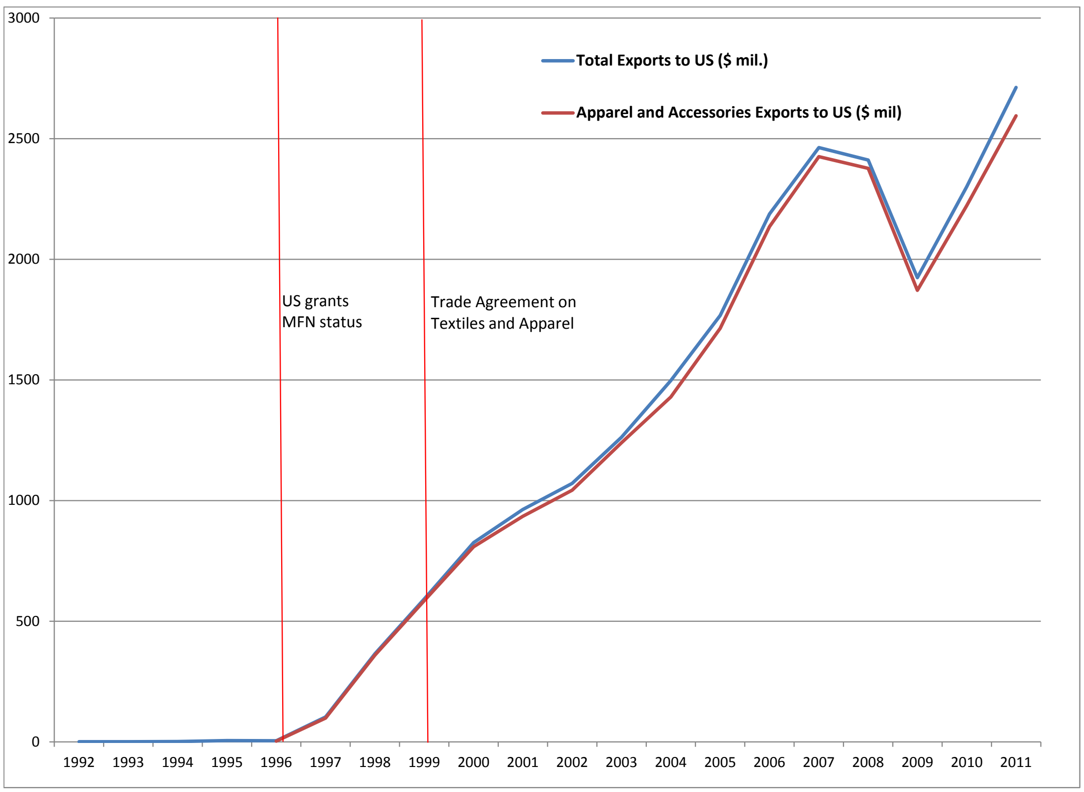
2.2.1 Background

Close to half a million people are employed in the garment export sector in Cambodia, and more than 80 percent of workers are young women (Garment Manufacturers Association in Cambodia, 2014). As shown in Figure 2.1, Cambodia's apparel exports have experienced significant growth in the last twenty years. In 2013, exports of apparel totaled 4.9 billion dollars, and accounted for 80 percent of exports and 20 percent of GDP (Garment Manufacturers Association in Cambodia, 2014). Close to half of apparel exports (41 percent) go to the United States, 35 percent to the European Union, and the rest to Japan, Canada and other markets (Garment Manufacturers Association in Cambodia, 2014). The world's largest clothing retailers source apparel from Cambodian factories.

The Cambodian garment industry started to develop after peace was restored and normal trade and political relations were re-established with the rest of the world[5]. The catalyst of the garment industry was the granting of Normal Trade Relations (or MFN) status by the United States. This agreement was signed by Congress in September 1996, and came into force in 1997. The tariff treatment of exports to the United States changed from "Column 2" tariffs to "General" tarrifs with ad-valorem export tariffs declining by 30 percentage points on average, and by 55 percentage points in garments. Unconstrained

[5]The communist Khmer Rouge regime took control of Cambodia in 1975 under the leadership of Pol Pot. The regime followed radical policies with the aim of transforming Cambodia into a "self-reliant" country, free of "foreign corruption". This entailed forced relocation of the entire urban population to villages, the creation of forced labor camps, abolition of all political and civil rights, private property, and education, as well as mass murders and executions Chandler (2014). It is estimated that approximately 1.7 million people (21 percent of the country's population) died as a result of executions, starvation and diseases from 1975 to 1979 (Cambodia Genocide Program, 2014). The regime fell after Vietnam invaded Cambodia in 1979 and a pro-Vietnamese government was established. The population returned to the cities, private property was restored, and schools were re-opened. In the late 1980's Vietnam withdrew from Cambodia. The first elections were held in 1993 and Cambodia became a constitutional monarchy Chandler (2014).

Figure 2.1: *Cambodia's Exports to the United States 1992-2011*



by quotas which dominated textile and apparel trade under the Multi-Fiber Agreement (MFA), Cambodia's exports to the United States surged rapidly from 4 million in 1996 to 100 million in 1997 and 300 million in 1998. Pressure from industry groups within the United States who were interested in limiting the surge in US imports from Cambodia and anti-sweatshop activists, who were concerned about working conditions, led the US Congress to draft a new trade agreement with Cambodia – known as the Textile and Apparel Trade Agreement (TATA) – which linked increased market access to improvement in labor and working conditions in export factories. The largest export categories (approximately 50 percent of exports) were brought under quota restrictions. The agreement stipulated that base quota allocations would increase by 6 percent each year and bonus quota increases of up to 15 percent annually (18 percent after 2001) would be granted conditional on the improvement in working conditions and enforcement of Cambodia's national labor laws. The annual quota increases were very generous relative to other countries, and allowed a continued growth of apparel exports (Dasgupta et al., 2001).

To be able to monitor and report the status and progress of labor conditions featured in TATA, the International Labor Organization (ILO) established Better Factories Cambodia (BFC), an entity whose mandate was to monitor and report on the status the labor and working conditions in the export factories[6]. Participation in the program was mandatory for all factories willing to export to the US under quota. The project was financed by the US government and involved the participation of the garment manufacturers' association and Cambodian union federations and ministries (Chiu, 2007). When TATA ended together with the MFA in January 2004, BFC continued to operate in the country and monitor the working conditions in the factory. Today, each factory who wants to receive an export license must be monitored by the BFC. International buyers can subscribe to BFC's service to access individual monitoring data on the factories. As international buyers were keen

[6]During factory visits, the BFC monitors interview managers and workers, review documents and make direct observations of factory conditions based on Cambodia's labor law and international labor law. The areas of labor law the are covered during visits are discrimination, forced labor, child labor, freedom of association and collective bargaining, compensation, working hours, contracts, and occupational safety and health (Better Factories Cambodia, 2014)

to dismiss their association with sweatshop work at the end of the 1990s, the continued growth of Cambodia's exports despite quantitative restrictions has often been attributed to the "sweatshop-free" image associated with TATA and BFC's establishment (Chiu (2007), Dasgupta et al. (2001)).

As of 2013, the membership of the Garment Manufacturers Association of Cambodia (GMAC) - a requirement for any factory engaged in exporting - was of 426 factories. The number of export factories increased by more than 10 fold since 1996 when the association was created. The majority of export factories are owned by entrepreneurs from China, Hong Kong, Taiwan and Korea. All fabrics and accessories used in Cambodia are imported because of the near-absence of upstream industries (United States Agency for International Development , USAID). More than 90 percent of the export factories are located in and around the capital of Phnom Penh, and concentrated in three districts of the Phnom Penh province (Dangkor, Mean Chey, Russey Keo). From Phnom Penh containers are transported to the deep-sea port of Sihanoukville, which is 230 kilometers away from Phnom Penh.

2.2.2 Women and Garment Work in Cambodia

As it is the case for most apparel export jobs, young women account for a disproportionate share of employment in export factories. The 2004 household survey data reveals that approximately 80 percent of all paid employees in apparel industries were women. More than 90 percent of them were young with ages between 15 and 30. Seventy percent of workers have never been married and still reside with their parents. Mean statistics are presented in table 2.1. The women typically originate from larger families (of more than 6 members) who are primarily engaged in rice cultivation. In most cases they represent the bread-winners of their families (83 percent of household members with paid jobs).

The majority of the women employed in garments reside in the villages on the outskirts of the capital and in the surrounding provinces. Figure 2.2 presents the geographical distribution of migrant workers in export factories in the Phnom Penh province based on the 1998 population census data. Proximity to the capital is associated with higher district

Table 2.1: *Summary Statistics of Garment Workers*

	Non-Garment Worker	Garment Worker
Age	35.4	23.7
Female	0.5	0.8
Never-married	0.3	0.71
Household Size	5.6	6.3
Years of schooling	6.1	6.41
Can Read	0.7	0.92
Mother's education	0.8	0.44
Hourly wage (median, 2004 Riels)	700	1,041
Share of number of days present at home	1.0	0.57
Rural	0.8	0.8
Relationship to Household Head (Son/Daughter)	0.3	0.74

Notes: Results based on 2004 Household Survey. Sample is all individuals with age above 15.

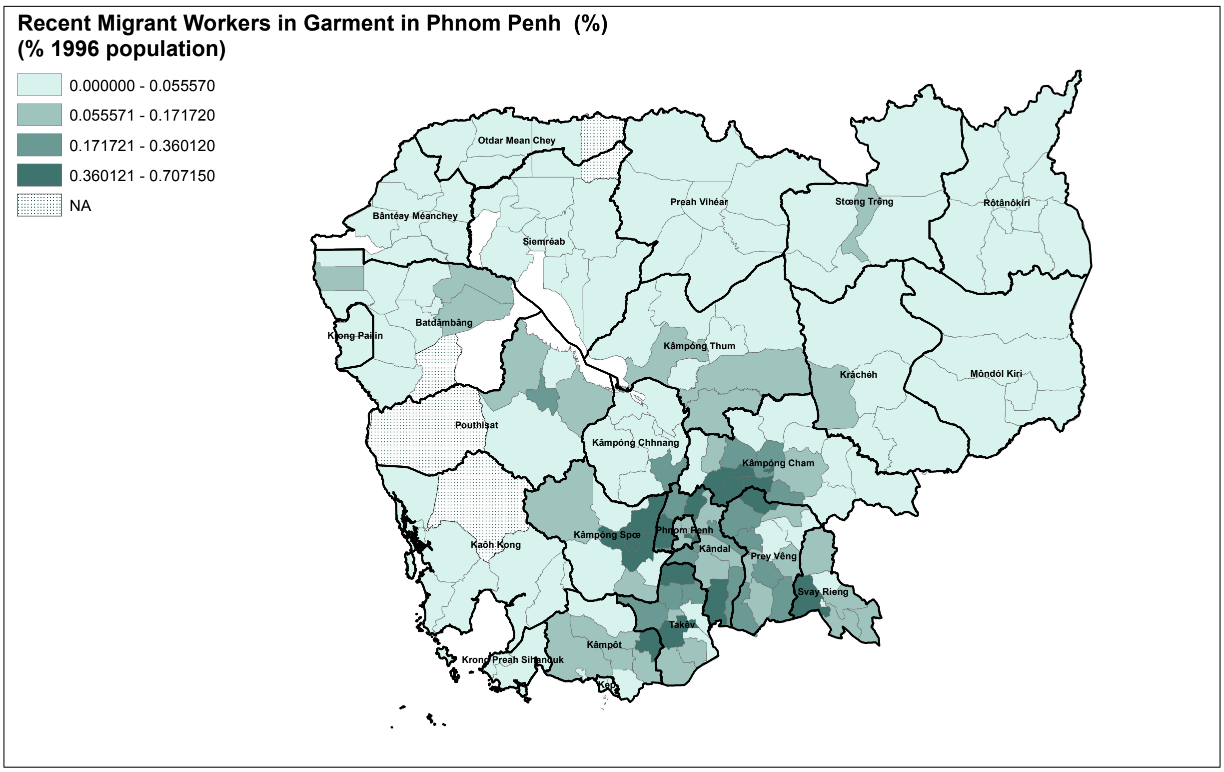
employment in garments. In the 2004 household survey, the questions regarding the number of days individual is present in the household reveal that garment workers are more likely than workers in other occupations to spend time away from the household. This is true primarily for workers whose families reside in villages from the provinces surrounding the capital.

The export garment sector represents an import source of paid employment for young women. Paid jobs represent only a quarter of employment, with more than half of young women reporting their main occupation to be unpaid family workers. Of paid jobs, apparel represents close to half of all employment opportunities. The rest of paid jobs are in agriculture and fisheries (18%), services (19%) and housework for other households (12%).

Export factory jobs are low-skilled jobs and require little education[7]. In the 2004 survey,

[7]Derks (2008) describes the factory selection process based on field research work: “When factories recruit new workers they tell them to spread the word among relatives and friends. When large numbers of new workers are sought, factories hang a sign outside the factory with information about their call for workers and the date and time of selection. Such an occasion attracts tens to hundreds of women, who stand for hours at the gate of the factory, waiting for someone to come out and start the selection procedure. A supervisor of a particular section in a factory will come out and choose potential workers randomly from the mass, choices more often based on appearance, height and healthy looks than on any demonstrated skills.[..] Factory managers claim, however, that the criteria for selection are not random or based on beauty. Instead, they are often related

Figure 2.2: *Migration to Phnom Penh Apparel Factories in 1998*



more than 90 percent of the women report being employed as machine operators and assemblers. Workers on average have completed 6 years of education – this is 0.3 years more than other women who are not employed in paid occupations, and more than a year less than women employed in other paid jobs. A simple selection equation of employment in garments presented in Table 2.2 shows that the probability of obtaining a job in a garment factory is negatively associated with any previous school attendance and years of schooling have a diminishing effect on the likelihood of obtaining a job in the factory. The impact of schooling after six years of education becomes negative. This implies that the returns to education with the purpose of obtaining a factory job are very high for primary education (essentially literacy) and much lower for secondary education. These relationships need to be interpreted with a lot of caution as both factory jobs and education may be jointly determined by unobserved individual ability for which we cannot control here.

Despite their low-skill content, export jobs in the garment sector pay significantly more than other jobs in the economy for the same level of education and experience. The positive relationship between wages and exporting has been well-documented in other countries. The median wage for a garment worker reported in the 2004 socio-economic survey was of 55 US dollars per month (0.26 dollars per hour), more than twice as much as wages paid in other jobs occupied by women. At a descriptive level, the household survey data show no correlation between a worker's level of education and wages within the garment industry. A simple Mincer regression presented in Table 2.2 of a worker's wage level while controlling for age and experience shows that there are no returns to education in the garments industry beyond the 6 percent increase in wages if the female worker has ever attended school. This is not the case for other jobs in the economy where an additional year of schooling contributes to 9 percent increase in wages. The last column of Table 2.2 shows that there are declining

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to the particular manufacturing procedures for which new workers are sought. For some procedures, such as knitting, height and literacy are important in order to be able to handle the machine and read the knitting patterns, whereas working in quality control does not require any specific skills or stature. Some factories conduct a second selection procedure, or test, after the initial one, when they take a closer look at the capacities of a woman, such as the ability to sew a straight line or handle a machine. When a woman passes this test, she will be further trained in a specific procedure."

Table 2.2: *The Relationship between Education and Garment Jobs and Wages*

	Individual is enaged in garments (=1)	Hourly wage, garment workers (ln)	Hourly wage, other waged workers(ln)
Female	0.00766***	-1.750**	-0.385
	(0.00259)	(0.739)	(0.271)
Years of schooling	0.00246***	-0.0385	0.0932***
	(0.000715)	(0.0483)	(0.0121)
Years of schooling ^2	-0.000105*		
	(5.66e-05)		
Ever attended School (=1)	-0.00492***	-0.316**	-0.0210
	(0.00138)	(0.144)	(0.0677)
Ever attended School (=1) x Female	-0.0247***	0.381**	-0.0663
	(0.00428)	(0.160)	(0.0896)
Years of schooling x Female	0.0155***	-0.0381	0.0115
	(0.00210)	(0.0438)	(0.0144)
Years of schooling ^2 x Female	-0.00100***		
	(0.000146)		
Observations	59,432	1,244	6,929
R-squared	0.054	0.233	0.240

Notes: The unit of observation is an individual. The specifications in columns (2) and (3) contain age, age-squared, female-age, female-age-squared, third-degree polynomial of experience and its interactions with female dummy. All standard errors are clustered at the district level. *** p<0.01, ** p<0.05, * p<0.1

returns to education in the garment industry, and positive returns to education in other sectors after controlling for age and experience. After obtaining a household diploma, wage levels in other professions, such as teachers, life sciences, other professionals and management jobs are on average higher than wages in the garment industry.

2.2.3 Conceptual Framework

The arrival of garments export jobs can affect the relative investments in education for girls through various channels. We discuss four of these channels below.

First, apparel export jobs may increase the desirability of investing in girls' education relative to boys' by increasing parents' perceptions of daughter's future earnings relative to her male siblings. This channel assumes that a woman's education increases the probability of obtaining a factory job and that there are returns to education in the garments industry. The returns to education channel is highlighted in Heath and Mobarak (2014) in the context of the garment industry in Bangladesh. The authors find that the arrival of garment factory jobs was associated with an increase in enrollment of girls relative to boys in the 5-10 age cohort.

However, export jobs may also increase the opportunity cost of staying in school if the skill content of these jobs is very low. It has been widely documented that export jobs pay higher wages than jobs in domestic firms. In Cambodia, export garment jobs pay more than twice on average relative to other jobs available to women in the economy. Atkin (2012) establishes this channel in the case of Mexico's export manufacturing expansion. In the case of Cambodia, education has a diminishing return on the likelihood of obtaining a job in the apparel factory which suggests that the desirability of enrolling girls in school should be highest for the first years of education, most likely in the 5-10 age cohort. The returns to staying in school decline with the years of accumulated schooling.The opportunity cost of staying in school for women after age 15 (the minimum age of working in a factory) should be very high. This suggests that in the context of Cambodia, the returns-to-education channel should be very strong for younger cohorts and not-existent for older cohorts of children. Moreover, this channel should affect all households in the provinces surrounding Phnom Penh, irrespective of whether they have a household member employed in the garment factory or not. We can use the sample of households with no female members at the eligible age to work in the factory (15 to 30) to test this channel.

A second channel is that a member working in garments raises total household income and this should increase investments in education for girls if girls education is a luxury good relative to boys' education. This channel can be easily tested by examining whether girls' likelihood of attending or staying in school relative to boys is increasing with household income in the sample of households with no member employed in a garment factory. The district fixed effects specification shows that girls' likelihood to be enrolled in school is

Table 2.3: *Children's School Enrollment and Household Income*

	Individual Is Currently Attending School		Individual Stayed in School	
	(1)	(2)	(3)	(4)
Household Income Per Capita (ln)	0.018***		0.003	
	(0.003)		(0.002)	
Female x Household Income Per Capita(ln)	0.003	0.006	0.007***	0.008
	(0.004)	(0.008)	(0.003)	(0.006)
Controls (for all panels)				
Female, Age, Age Squared Controls	Y	Y	Y	Y
Female-Age, Female Age-squared Interactions	Y	Y	Y	Y
Mother Education, Household Size	Y	N	Y	N
Mother Education -Female, Household Size -Female Interactions	Y	Y	Y	Y
Household Fixed Effects	N	Y	N	Y
Clustering (district, 79)	Y	Y	Y	Y
Observations	7,550	7,550	6,921	6,921

Notes: The unit of observation is an individual i in household h in district d.The sample includes households with no member employed in the garment industry. The sample is restricted to individuals below 15 years of age. The controls included are indicated in the table by Y(yes) or N(No). Coefficients are reported with standard errors clustered in parentheses clustered at the district level, *** p<0.01, ** p<0.05, * p<0.1.

higher in households with higher income per capita. But the gender-income-per-capita interaction is not significant in the household fixed effect specification, suggesting that when holding (unobserved) family background constant, daughters are not more likely than sons to be enrolled in school, partially refuting the luxury good hypotheses.

Third, by increasing female-specific income garment jobs may increase older daughter's bargaining power within the household. If older female siblings have a higher preference for investing in their sisters education, garment jobs will tend to increase the investment in education for girls. This mechanism has been highlighted by (Qian, 2008) and Duflo (2003). This explanation is most consistent with with non-unitary model of the household. The unitary model makes the strong prediction that an increase in income should have the same effect on household consumption and investment regardless of which member of the household brings home the additional income. A test of this channel entails examining what happens with household investment and consumption in response to male and female income increases. Different responses of investments in education of girls and boys in response to shocks to male and female income will rule out the second channel.

Finally, older sisters and other young women from the village who are employed outside the household in a formal job may represent role models for their younger siblings. This may influence their attitudes and self-confidence, which in turn may affect their likelihood of staying in school. Existing research has shown that exposure to strong female role models can alter the behavior of women (Beaman et al. (2012), Jensen and Oster (2009)). Under the assumption that role models are not restricted to the household, this channel can be ruled out by looking at the relative enrollment rates in household with no eligible member to work in the factory. Because the likelihood of working in the factory is positively correlated with the distance to the Phnom Penh garment cluster, distance should also affect the presence of role models factory workers.

The first, second and last explanations are consistent with both the unitary and non-unitary models of household decision making. The first and fourth explanations can be ruled out by looking at the relative propensity of girls to be enrolled in school relative to boys in households in which all female members have passed the prime age of working in the factory. Proximity to the factory should positively affect the returns to investing in girls irrespective of whether an older sibling works in the factory. Similarly, young girls should be exposed to female factory workers irrespective of whether an older sibling works in the factory. To be able to distinguish between the second and third explanation one needs to use an exogenous increase in male generated income and test its effect on the education of female and male siblings within the household. We are not aware of shocks that increase the income opportunities of Cambodian men. But we will make use of the information contained in the part of the households in the sample in which a son is employed in the apparel industry.

2.3 Empirical Strategy

2.3.1 Data and Samples

The data used to investigate the effect of factory jobs on siblings education comes from Cambodia's Socio-Economic Survey (CSES) of 2004 conducted by National Institute of Statistics[8]. The survey was conducted in a nationwide representative sample of 15,000 households within 900 sampling units (villages).

The 2004 data allows us to identify the households with members employed in the apparel industry and to observe the individual education variables at the household level. Importantly, the survey contains information on all household members irrespective of whether they do not reside in the household. This is very important in the context of Cambodia because the garment factory workers migrate temporarily to Phnom Penh to take the jobs in the garment factories. Our primary dependent variable of interest is an indicator variable for whether an individual residing in a given household is currently enrolled in school. We use a secondary outcome variable for whether an individual continues to attend school provided they have attended school in the past. This second dependent variable measures the likelihood of individuals of staying in school and applies to a fewer number of individuals than the first dependent variable.

There are 1,295 individuals in the survey who report the industry of their main occupation to be manufacture of apparel, and 916 households in which at least one household member is employed in apparel. We call these households "garment" households. Approximately 90 percent of the households are within 150 kilometers from the center of Phnom Penh, and we restrict the sample to these districts. This ensures that the households and individuals are more comparable to one another. For the purpose of the instrumental variable analysis, we restrict our sample to households in which at least one female member

[8]The CSES is a household survey with questions to households and individual household members, including modules on education and literacy, current economic activity, migration, housing conditions, durable goods, construction activities, nutrition, fertility and child care, child feeding and vaccination, health of children, mortality health and illness. The Survey has been previously conducted in the years 1993/94, 1996, 1997 and 1999. Since 2007 the survey has been conducted annually.

Table 2.4: *Summary Statistics of Variables Used in the Regression*

	Currently Continuing School	Currently Attending School	Female	Age	Years of Schooling	Household Size	Mother's Education
Male	0.96	0.86	.	8.53	3.22	6.22	0.45
	(0.19)	(0.34)	.	(4.43)	(2.51)	(1.92)	(0.45)
			.				
Female	0.92	0.84	1	8.98	3.56	6.22	0.46
	(0.27)	(0.37)	.	(4.69)	(2.69)	(1.94)	(0.45)
Total	0.94	0.85	0.5	8.76	3.39	6.22	0.46
	(0.24)	(0.35)	(0.50)	(4.57)	(2.61)	(1.93)	(0.45)

Notes: All individuals with ages below 15 in the sample of households with at least one female member aged 15 to 30.

is young, i.e in the age cohort 15 to 30, and to individuals below working age. We also exclude from the sample those households who have migrated after 1993 to ensure that our results will not be contaminated by migrant families which respond endogenously to the expansion of employment opportunities for girls.

The second source of data are distances from the district towns to Phnom Penh. These distances were obtained using Google Maps data, and are calculated from the district capital to the center of Phnom Penh. Ideally, one would use the distance from the villages where the household resides to the closest export factory, but this data is not yet available.

2.3.2 Empirical Specification

We investigate the impact of having a female household member employed in the garment industry by estimating the following empirical specification:

$$S_{ihd} = \delta_d + \beta_g G_{ihd} + \beta_f G_{ihd} Female_i + X_i \Gamma + X_i Female_i \Theta + X_h \Phi + X_h Female_i \Psi + \varepsilon_{ihd} \quad (2.1)$$

The index i denotes individuals, h denotes households, and d denotes districts. The outcome variable S_{ihd} is an indicator variable for whether individual i in household h in district d is currently attending school. We also investigate the outcome of continued school attendance, which is the probability of attending school given that the individual has previously attended school. G_{ihd} is an indicator variable for whether individual i residing in household h in district d has a female employed in the garment industry; X_i is a vector of individual characteristics such as gender, age, and age-gender and interactions; X_h is a vector of household characteristics such as household size and the level of education of the mother, which might influence the propensity of an individual in the household to be enrolled in school; δ_d is a district fixed effect which controls for unobserved geographical characteristics which may affect the enrollment of children in school. The coefficient β_g measures the average propensity of being enrolled in school for a child residing in a household with at least one female member working in the apparel industry, and the coefficient β_f measures the differential propensity of being enrolled in school if the gender of the child is female.

We also estimate equation 2.1 using household fixed effects. This entails that the comparisons of the propensity to be enrolled in school are only based on siblings within the same household. Holding household background constant potentially increases the precision of our estimates, but it also entail a further restriction of the sample to larger households, which have at least one male and one female child. The effect of G_{ihd} and the controls X_h will get absorbed by the household fixed effect. In this specification, β_f measures the differential propensity to be enrolled in school for a female sibling relative to her male sibling *within* the same household.

The main challenge in identifying the causal effect of apparel export jobs on the education of siblings arises from joint determination. If unobserved household characteristics influence both a household's propensity to send a daughter to work in an export factory and preferences for education of younger female siblings relative to male siblings, the OLS estimate will be biased. One such example is a high bargaining weight of the mother within the household. A strong mother would be able to both negotiate the migration of an older daughter to Phnom Penh to work in the factory and the continued enrollment of younger daughters into school. Its omission from the regression would cause the OLS estimate to be biased upwards.

The selection bias can be avoided by finding an instrument for household's propensity to send a daughter to work in an apparel factory. Because the majority of garment workers need to migrate from their villages to work in a garment factory, an instrument that generates exogenous variation in migration costs is a good candidate. We use the distance from the district where the household resides to the closest garment cluster in Phnom Penh to instrument for a household's propensity to send a household member to work in the factory. The map in Figure 2.2 shows that proximity to the capital is strongly associated with individual's propensity to migrate to take a job in the export factory. As discussed earlier, we apply this instrument within the sample of households with at least one female member in the age cohort of 15 to 30, which is the prime ages of working the garment export factories, while further restricting the sample to provinces surrounding the capital. Causal inference requires the assumption that distance to the closest garment cluster in Phnom Penh within the sample of households with a woman at eligible age only affects the propensity of young girls to be enrolled in school *relative* to their male siblings through the older female sibling's propensity of working in the apparel industry. For the instrument to satisfy the exclusion restriction, it is necessary to restrict the sample to sibling below the minimum working age in the garment factories which is 15[9]. Otherwise, assuming that export factory work increases the opportunity costs of schooling, proximity to the factory directly affects the educational choices of children at working age.

In a two-stage least squares(2SLS) framework, equation 2.1 is the second stage of the 2SLS system and equation 2.2 below is the first stage

$$G_{ihd} = \alpha ln(distPP_d) + X_i\Gamma + X_h\Phi + \varepsilon_{ihd} \tag{2.2}$$

where $ln(distPP_d)$ is the natural log of the distance to Phnom Penh from the district

[9]According to the regulations set out by Better Factories Cambodia, factories that employ workers under age 18 are subject to additional requirements such as, maintaining a register of workers under age 18, getting consent from their guardians for them to work, etc. In practice, the detection of underage work is problematic because Cambodia does not maintain a universal birth registration system and and falsification of age-verifying documents is common. However, the monitoring done by BFC (usually through visual checks) ensures that a minimum age is requirement is largely observed by the factories. The existence of a monitoring body most likely contributes to the reduction of underage work in the export factories

where individual i belonging to household h resides. A natural concern for the exclusion restriction is that the proximity to the garment cluster affects the relative propensity of girls below working age to be enrolled or stay enrolled in school though channels other than the propensity of having an older female sibling employed in the factory. As discussed earlier, proximity to the factory may directly affect educational investments of girls relative to boys by changing the returns to investing in school and by providing women with role models that my directly change their beliefs and behavior. These channels should be active for both girls residing in eligible households and girls residing in non-eligible households. In tables 2.7 and 2.8 we estimate the reduced form of 2.2 including all individuals below the minimum working age in households without a female member between ages 15 and 30, and then further restricting the sample to individuals below the minimum work age. The results show that educational choices of siblings in families that do not have at least one eligible woman to work in the factory are not affected by proximity to the factory. The second threat to the exogeneity assumption is that the proximity to Phnom Penh also affects the likelihood of older female siblings of obtaining paid jobs that are not in the garment sector. One such example would be work in the government, which accounts for a quarter of jobs for women in that age group. We show that the distance to Phnom Penh measure is only weakly associated with other paid employment opportunities for women, and that female paid work outside of the garment industry has no effect education of younger siblings.

2.4 Estimation Results

OLS Estimates

The results of estimating equation 2.1 by OLS are presented in Table 2.5 panel A. The first two columns present the results of using the dummy variable that an individual is currently enrolled in school, using the district and household fixed effects specifications. The last two columns use as outcome a dummy variable for whether an individual is currently enrolled in school given that they previously attended school.The results in the first column show that boys in households with at least one female member working in the apparel industry are less likely to attend school than boys in households with no female member engaged in apparel, but the results are not statistically significant. The coefficient on the gender interaction is positive, and again not significant. This is true for both the district and household fixed effects specifications. The OLS results are significant when investigating the likelihood of staying in school, which restricts the sample to children who have previously attended school. The effect of having a household female member in garments is again negative suggesting that boys in these households are more likely to drop out of school.

The coefficient on the female gender interaction is positive, significant, and of larger magnitude. The total effect of a female member working in apparel is positive on female siblings. Younger female siblings are 2 percentage points more likely to be enrolled in school if a a female household member is working in the factory. These results are robust to using household fixed effects which compares male and female siblings within the same household. The female gender interaction in the household fixed effects specification is larger - this is to be expected since the estimation is based on a sample composed of larger families (who have both a female and a male sibling) which may be poorer in average. For these poorer families, the employment of a daughter in an export factory might have a larger effect on the education of girls.

First Stage and Reduced Form

The reduced-form and first-stage estimates of equation 2.2 are shown in panels B and D of Table 2.5. The first stage estimates in panel D, columns (1) show that there is a strong positive relationship between the instrument and the likelihood that a household has a female member engaged in apparel production. The Kleibergen-Paap statistic is above 20 for the household fixed effects specifications but below 10 when using district fixed effects. This suggests that we should not worry about our estimates being biased by weak instruments in the household fixed effects specifications, but that we should interpret the 2SLS estimates with caution in the district fixed effects specification. A household living 10

Table 2.5: *The Impact of Factory Work on Siblings' Education: Individuals Below 15 Years Old*

	Dependent Variable = Individual Is Currently Attending School		Dependent Variable = Individual Stayed in School	
	(1)	(2)	(3)	(4)
Panel A: OLS Estimates				
Household Has Female Member in Apparel Job	-0.017		-0.031	
	(0.022)		(0.020)	
Female x Household Has Female Member in Apparel Job	0.030	0.048	0.058**	0.101**
	(0.029)	(0.050)	(0.026)	(0.046)
Panel B: Reduced Form Estimates				
ln (Distance to Phnom Penh)	-0.015		0.007	
	(0.013)		(0.009)	
Female x ln (Distance to Phnom Penh)	-0.021**	-0.031**	-0.026***	-0.028**
	(0.011)	(0.015)	(0.010)	(0.012)
Panel C: 2SLS Estimates				
Household Has Female Member in Apparel Job	0.214		-0.096	
	(0.190)		(0.125)	
Female x Household Has Female Member in Apparel Job	0.384*	0.407**	0.400**	0.344***
	(0.208)	(0.159)	(0.168)	(0.108)
Panel D: First Stage Estimates				
ln (Distance to Phnom Penh)	-0.066***		-0.067***	
	(0.014)		(0.014)	
Female x ln (Distance to Phnom Penh)		-0.076***		-0.082***
		(0.023)		(0.026)
Kleibergen-Paap F Statistic	6.02	22.265	6.711	21.321
Controls (for all panels)				
Female, Age, Age Squared Controls	Y	Y	Y	Y
Female-Age, Female Age-squared Interactions	Y	Y	Y	Y
Mother Education, Household Size	Y	N	Y	N
Mother Education -Female, Household Size -Female Interactions	Y	Y	Y	Y
Household Fixed Effects	N	Y	N	Y
Clustering (district, 79)	Y	Y	Y	Y
Observations	4,066	3,140	3,724	2,794

Notes: The unit of observation is an individual *i* in household *h* in district *d*. The sample includes 2942 households surveyed in the year 2004. The sample includes households with at least one female member between the ages 15 and 30. The controls included are indicated in the table by Y(yes) or N(No). Coefficients are reported with standard errors clustered in parentheses clustered at the district level, *** p<0.01, ** p<0.05, * p<0.1. In panel D we report first-stage Kleibergen-Paap F-Statistics.

kilometers away from the nearest garment cluster in Phnom Penh is 13 percentage point (half a standard deviation) more likely to have a female household member employed as a factory worker than a household living 100 kilometers away. These predicted magnitudes are in line with what we would expect. The share of households involved in garments declines by 10 percentage points as we move from a district situated 10 kilometers away to a district situated 100 kilometers away from Phnom Penh.

In panel B, the reduced-form effects of our distance instrument on the outcomes of interest show that proximity to the Phnom Penh garment cluster is positively and statistically significant associated with higher relative likelihood of girls to be enrolled relative to boys in both in both the within-district and within household specification.

2SLS Estimates

The 2SLS estimates of equation 2.2 are presented in Panel C of Table 2.5. According to the estimates a household with at least one female member employed in a garment factory increases the likelihood of girls enrollment in schools relative to their brothers by 40 percentage points and the likelihood of staying in school by 30 percentage points in the fixed effects specification. These magnitudes are around one standard deviation for both outcomes variables, and significantly larger than the OLS estimates. This suggests that the OLS coefficients were downward biased. One reason for the downward bias might be that households that are poorer and hence less likely to be able to send their younger daughters to school may also be more likely to send a daughter to work in the garment factory. As it is the case for all instrumental variable estimates, our 2SLS estimates reflect the average effect on observations that respond or comply to our distance instrument, namely the *local average treatment effect* (Angrist and Imbens, 1994). In the current setting, the compliers are households who send an older daughter to work in the factory because of its proximity to Phnom Penh. Our estimates are not driven by households whose decision to send an older daughter to work in the factory is not affected by the proximity to the factory.

Mechanisms

The conceptual framework presented in section 2.2.3 identified four main channels through which the employment of an older female sibling in an export factory may differentially affect the investment in education of female relative to male siblings. In this section we present evidence to support or rule out some of these channels.

The differential returns to the education of female and male siblings can be ruled out in two ways, depending on the assumptions regarding the information households have regarding factory jobs. One scenario is that households only have information on the education requirements to obtain a job in the factory if one household member works in the factory. The second scenario is that proximity to the export clusters is positively correlated with information on the education requirements of export jobs, irrespective of whether one of the household members works in the factory.

Under the first information scenario, we present evidence that rules out the differential returns to the education of female and male siblings by looking at heterogeneous effects in the 5-9 and 10-15 age cohorts. As discussed in section 2.2.3, the higher relative propensity to attend school of younger sibling could be a response to the returns to education channel if it shows up for the young cohort of siblings. We find that the positive impact of female factory work on female household members are concentrated in the 10 to 15 age cohort, and they are non-existent in the 5 to 9 age cohort. The results for the 10 to 15 age cohort are presented in Table 2.6. The magnitude of the 2SLS coefficients in panel C is almost twice as large in magnitude relative to the coefficients reported in Table 2.5. The estimated coefficients in the 5 to 9 age cohort are not statistically significant. For the second information scenario, we present evidence showing that proximity to the Phnom Penh garment cluster does not affect the relative enrollment rates of female siblings in households who do not have a young female member. These placebo results are presented in Table 2.7 and Table 2.8 for all individuals and the 10 to 15 age cohort. The gender interaction coefficient is close to zero and not significant for both the within-district and within household specifications, for both outcome variables.

Table 2.6: *The Impact of Factory Work on Siblings' Education: Individuals in the 10 - 15 Age Cohort*

	Dependent Variable = Individual Is Currently Attending School		Dependent Variable = Individual Stayed in School	
	(1)	(2)	(3)	(4)
Panel A: OLS Estimates				
Household Has Female Member in Apparel Job	-0.044*		-0.042	
	(0.026)		(0.026)	
Female x Household Has Female Member in Apparel Job	0.075**	0.103	0.068**	0.130
	(0.037)	(0.095)	(0.033)	(0.089)
Panel B: Reduced Form Estimates				
ln (Distance to Phnom Penh)	0.007		0.012	
	(0.015)		(0.013)	
Female x ln (Distance to Phnom Penh)	-0.041***	-0.066**	-0.039***	-0.049*
	(0.014)	(0.027)	(0.012)	(0.026)
Panel C: 2SLS Estimates				
Household Has Female Member in Apparel Job	-0.115		-0.187	
	(0.238)		(0.189)	
Female x Household Has Female Member in Apparel Job	0.552**	0.859***	0.532***	0.567***
	(0.219)	(0.282)	(0.197)	(0.206)
Panel D: First Stage Estimates				
ln (Distance to Phnom Penh)	-0.070***		-0.071***	
	(0.015)		(0.015)	
Female x ln (Distance to Phnom Penh)		-0.077*		-0.087*
		(0.039)		(0.046)
Kleibergen-Paap F Statistic	12.645	10.688	6.711	12.32
Controls (for all panels)				
Female, Age, Age Squared Controls	Y	Y	Y	Y
Female-Age, Female Age-squared Interactions	Y	Y	Y	Y
Mother Education, Household Size	Y	N	Y	N
Mother Education -Female, Household Size -Female Interactions	Y	Y	Y	Y
Household Fixed Effects	N	Y	N	Y
Clustering (district, 79)	Y	Y	Y	Y
Observations	2,761	1,790	2,702	1,722

Notes: The unit of observation is an individual *i* in household *h* in district *d*. The sample includes 2942 households surveyed in the year 2004.The sample includes households with at least one female member between the ages 15 and 30. The sample is restricted to individuals above 10 years of age. The controls included are indicated in the table by Y(yes) or N(No). Coefficients are reported with standard errors clustered in parentheses clustered at the district level, *** p<0.01, ** p<0.05, * p<0.1. In panel D we report first-stage Kleibergen-Paap F-Statistics.

Table 2.7: *Enrollment in School in Households with No Female Household Member in the 15-30 Age Cohort: Individuals Below 15 Years Old*

	Dependent Variable = Individual Is Currently Attending School		Dependent Variable = Individual Stayed in School	
	(1)	(2)	(3)	(4)
Reduced Form Estimates				
ln (Distance to Phnom Penh)	-0.022***		-0.000	
	(0.008)		(0.005)	
Female x ln (Distance to Phnom Penh)	0.002	0.011	-0.001	0.001
	(0.008)	(0.014)	(0.005)	(0.009)
Controls (for all panels)				
Female, Age, Age Squared Controls	Y	Y	Y	Y
Female-Age, Female Age-squared Interactions	Y	Y	Y	Y
Mother Education, Household Size	Y	N	Y	N
Mother Education -Female, Household Size -Female Interactions	Y	Y	Y	Y
Household Fixed Effects	N	Y	N	Y
Clustering (district, 79)	Y (79)	Y (79)	Y (79)	Y (79)
Observations	3,758	3,758	2,479	2,479

Notes: The unit of observation is an individual *i* in household *h* in district *d*. The sample includes 2008 households surveyed in the year 2004.The sample includes households with no female member between the ages 15 and 30. The controls included are indicated in the table by Y(yes) or N(No). Coefficients are reported with standard errors clustered in parentheses clustered at the district level, *** p<0.01, ** p<0.05, * p<0.1.

The role model channel discussed in section 2.2.3 can be fully ruled out with the same placebo tests presented in Table 2.7 and Table 2.8, under the assumption that girls' behavior and attitudes can be changed by non-sibling role models. The economic literature on the role-model effect does not distinguish between family and non-family role models, but most of the evidence in this area comes that role models outside shape the educational and career choices of young girls.

As discussed in section 2.2.3, to be able to distinguish between the second channel, (the investments in education of girls is a luxury good) and the third channel (that increased female income is associated with increased bargaining power of women within the household) one would need to test whether changes to male income have the same effect on the educational investment of girls relative to boys, as increases in female income. Unfortunately, we are not aware of shocks to male specific income over the sample period in Cambodia.

We can make progress in disentangling these two channels by using the information

Table 2.8: *Enrollment in School in Households with No Female Household Member in the 15-30 Age Cohort: Individuals Individuals in the 10 - 15 Age Cohort*

	Dependent Variable = Individual Is Currently Attending School		Dependent Variable = Individual Stayed in School	
Reduced Form Estimates				
ln (Distance to Phnom Penh)	-0.009		-0.002	
	(0.008)		(0.008)	
Female x ln (Distance to Phnom Penh)	-0.000	0.018	-0.002	-0.006
	(0.008)	(0.030)	(0.007)	(0.022)
Controls (for all panels)				
Female, Age, Age Squared Controls	Y	Y	Y	Y
Female-Age, Female Age-squared Interactions	Y	Y	Y	Y
Mother Education, Household Size	Y	N	Y	N
Mother Education -Female, Household Size -Female Interactions	Y	Y	Y	Y
Household Fixed Effects	N	Y	N	Y
Clustering (district, 79)	Y (79)	Y (79)	Y (79)	Y (79)
Observations	2,529	2,529	2,479	2,479

Notes: The unit of observation is an individual *i* in household *h* in district *d*. The sample includes 1667 households surveyed in the year 2004.The sample includes households with no female member between the ages 15 and 30. The sample is restricted to indviduals with ages betwen 10 and below 15. The controls included are indicated in the table by Y(yes) or N(No). Coefficients are reported with standard errors clustered in parentheses clustered at the district level, *** p<0.01, ** p<0.05, * p<0.1.

on households with a male member employed in the factory. Under the assumption that male income gains from garment factory work are of the same magnitude as female income gains, we can test whether male income opportunities affect investment in girls in a similar manner to female income opportunities. To be able to explore these effects, we expand the sample to include households with at least one young member who is male (between ages 15 and 30). Within this sample we identify households with at least one“eligible” man but no “eligible” woman. This is the sub-sample of households eligible to send a male migrant member to work in the garment industry, but not a female garment migrant. We estimate the within-household reduced form specification in the new sample.

$$S_{ihd} = \delta_h + \beta_1 M_{ihd} Female_i + \beta_2 M_{ihd} Female_i ln(distPP_d) + \\ \beta_3 Female_i ln(distPP_d) + X_i Female_i \Theta + X_h Female_i \Psi + \varepsilon_{ihd} \tag{2.3}$$

Table 2.9: *The Impact of Male Apparel Work on Siblings' Education: Individuals Below 15 Years Old*

	Dependent Variable = Individual Is Currently Attending School	Dependent Variable = Individual Stayed in School
	(2)	(4)
Panel A: OLS Estimates		
Female x Household Has Female Member in Apparel Job	0.050	0.073
	(0.049)	(0.046)
Female x Household Has Male Member in Apparel Job	0.014	0.005
	(0.060)	(0.051)
Panel B: Reduced Form Estimates		
Female x ln (Distance to Phnom Penh)	-0.032**	-0.028**
	(0.015)	(0.012)
Female x Household Has Eligible Men (age 15-30) No Eligible Women	-0.182	-0.153*
	(0.140)	(0.089)
Female x Household Has Eligible Men (age 15-30) No Eligible Women x ln (Distance to Phnom Penh)	0.042	0.044*
	(0.035)	(0.024)
Controls (for all panels)		
Female, Age, Age Squared Controls	Y	Y
Female-Age, Female Age-squared Interactions	Y	Y
Mother Education, Household Size	N	N
Mother Education -Female, Household Size -Female Interactions	Y	Y
Household Fixed Effects	Y	Y
Clustering (district, 79)	Y	Y
Observations	5,715	5,263

Notes: The unit of observation is an individual I in ousehold h in district d. The sample includes 3415 households surveyed in the year 2004.The sample includes households with at least one member between the ages 15 and 30. The controls included are indicated in the table by Y(yes) or N(No). Coefficients are reported with standard errors clustered in parentheses clustered at the district level, *** p<0.01, ** p<0.05, * p<0.1.

where M_{ihd} is a dummy variable which equals 1 if individual i resides in a given household h with at least one man in the age cohort of 15 to 30 but no woman in this age cohort. If the household is unitary and the identity of the income recipient does not matter then $\beta_2 = \beta_3$.

The results of estimating this equation are presented in Table 2.9. Panel A presents the OLS results in the new sample of all households with at least one member in the age cohort 15 to 30. Panel B presents the reduced form results from estimating equation 2.3. The coefficient β_2 is negative and significant for both outcome variables as in the earlier specifications. The coefficients β_3 are positive, significant and of larger magnitude (for the second outcome variable) suggesting that girls in the households eligible to send only male workers to work in the factory are not more likely to stay in school relative to their male siblings. Meanwhile, proximity to the garment clusters positively affects the relative likelihood of female siblings to be enrolled in school when the household has at least one eligible member to work in the factory. While not definitive, this evidence is suggestive of the bargaining power channel and of a non-unitary household model.

2.5 A Triple Difference Approach

A concern with the estimation strategy described in section 2.3 is that there might be differences in the relative propensity of school enrollment for female and male siblings in households with at least one "eligible" female member and which are positively correlated with the proximity to the garment factories, which precede the granting of MFN status in 1996 by the US. As shown in Figure2.1, Cambodia's exports of apparel to the US witnessed a sharp increase in 1997 after the MFN status were granted and tariffs on the exports of apparel products fell by 55 percentage points. The value of exports increased from 4 million in 1996 to 1.4 billion dollars in 2004. We can account for any pre-existing differences in the relative propensity to be attending school by taking advantage of the school enrollment data prior to 1996, and using a triple difference estimation strategy which compares the propensity of school enrollment of girls relative to boys within the same household (first difference), before and after the granting of MFN status (second difference) in districts with varying proximity to the Phnom Penh garment cluster (third difference). We apply the triple-difference estimator within the sample of household with and without an eligible woman to work in the factory.

To summarize we estimate the following equation on an individual i residing in household h in district d and in time period t:

$$S_{ihdt} = \delta_{ht} + \beta_1 Female_i + \beta_2 I_t^{(1=2004)} Female_i + \beta_3 ln(distPP)_d Female_i + \\ \beta_4 ln(distPP)_d Female_i I_t^{(1=2004)} + X_{ht} Female_i \Gamma + \varepsilon_{ihdt} \quad (2.4)$$

where δ_{ht} is a household fixed effect which will vary by year because the data is a repeated cross-section, $I_t^{(1=2004)}$ is a dummy for year 2004, and X_{ht} is a vector of household variables such as size and number of siblings. The coefficient β_4 measure the change in the enrollment of girls relative to their male siblings from 1996 to 2004 in households located at varying proximity from the garment factories. The analysis so far predicts that β_4 should be negative - female siblings should be more likely to be enrolled in school relative to their male siblings in 2004 after the tariff drop in districts that are closer to the export factories. Ideally we would want to take advantage of more years prior to the reform to make sure there are no preexisting trends in the outcome variable before the trade reform. However, the one household survey data available is from 1993 and that does not contain districts identifiers.

The results of estimating equation 6.1 are presented in Table 2.10. The first two columns present the estimation results with the sample restricted to household with at least one female household member of eligible age to work in the factory (15-30) in the age cohorts 5-9 and 10 to 15. The last two columns contain the estimation results for households with no woman of eligible age. The coefficient β_4 is negative and significant. The total difference in enrollment between male and female siblings in 4 is equal to the sum of the coefficients β_3 and β_4, namely -0.068. This magnitude is almost equal and certainly within the confidence

Table 2.10: *The Effects of Garment Jobs on School Enrollment: Pre and After Comparisons*

	Dependent Variable = Individual Is Currently Attending School			
	Household with Female Member with Age 15 to 30		Household with No Female Member with Age 15 to 30	
	Age Cohort 10-15	Age cohort 5-9	Age Cohort 10-15	Age cohort 5-9
	(1)	(2)	(3)	(4)
Female	-0.607	0.885	0.111	0.148
	(1.559)	(1.826)	(1.587)	(1.043)
Post (Year=2004) x Female	0.754	0.952	0.316	0.604
	(0.552)	(0.778)	(0.382)	(0.627)
Female x ln (Distance to Phnom Penh)	0.030	0.069	-0.001	0.008
	(0.033)	(0.079)	(0.025)	(0.043)
Post (Year=2004) x Female x ln (Distance to Phnom Penh)	-0.098**	-0.019	0.029	-0.001
	(0.045)	(0.103)	(0.037)	(0.072)
Observations	4,424	2,830	4,542	3,601
R-squared	0.722	0.891	0.738	0.852

Notes: The unit of observation is an individual *i* in household *h* in district *d*. The sample includes households with at least one female member between the ages 15 and 30. All regressions contain household fixed effects and controls for age, age squared, female indicator interacted with age and age squared, female indicator interacted with share of siblings in household, household size, mother's education. Standard errors clustered at the district level (79 clusters). *** p<0.01, ** p<0.05, * p<0.1

interval of the reduced form coefficient from equation 2.2 presented in Table 2.6, panel B, column 2. This suggests that the pre-reform differences in the relative propensity of attending school for girls in the age cohort 10 to 15 in households residing close to Phnom Penh were actually negative as captured by the coefficient β_3 in equation 6.1. While this coefficient is positive, it is not statistically significant suggesting that the within household differences in enrollment of female and male siblings is not different from zero. Consistent with the previous estimation results, we find no effect for young cohorts, aged 5 to 10, and no effect for children residing in households with no female member of eligible age.

2.6 Conclusion

This paper studied the impact of female factory work on household educational investments in the context of Cambodia. We compared the propensity to attend school of a female sibling relative to her brother in households with varying proximity to the export garment factories. We found that in households who were induced to send a female member to work in the garment factories by the proximity to the factories, young girls are one standard deviation more likely to attend school relative to their male siblings. These effects are only significant for the age cohort 10-15. A triple difference estimation strategy was used to ensure that these differences in enrollment did not exist prior to 1997, when Cambodia obtained MFN status from the US, and exports took off.

The evidence is consistent with qualitative evidence which suggests that part of the income obtained from the factory is directed towards the education of younger siblings. This suggests that by increasing income opportunities for young women, export factory work may increase the bargaining power of older daughters within the household. Because these women have different preferences for investing in their female and male siblings, export factory work is associated with higher investment in education for young female siblings. While the evidence is suggestive for the increased bargaining power channel, an alternative channel in which girls' education is a luxury good (possibly because of existing norms regarding the role of women within the household) cannot be fully rules out without an equal-sized shock to male income.

Interestingly, we find no effect on the arrival of garment jobs on the investments in girls' relative propensity to enroll in school in households with no female member of eligible age to work in the garment factory and residing in the neighboring provinces. This rules out the channel that garment jobs alter the relative return to investing in girls' schooling. This channel was identified by Heath and Mobarak (2014) in the case of garment factory expansions in Bangladesh. Oster and Millet (2013) and Jensen (2010) also found that the arrival of IT service jobs in India increases girls schooling. One explanation for why the return in channel is not present here is that the export garment jobs in Cambodia are very low-skilled jobs which require little or no education. This suggests that the expansion of export manufacturing in the developing world will have different effects on young girls depending on the skill content required for the product, and the average education levels for girls in those countries.

Chapter 3

The Impacts of Fair Trade Certification: Evidence From Coffee Producers in Costa Rica[1]

3.1 Introduction

Fair Trade (FT) certification offers consumers the opportunity to help lift farmers in developing countries out of poverty. The appeal of Fair Trade to ethically-minded consumers is illustrated by the impressive growth of Fair Trade certified imports over the past decade. Since its inception in 1997, sales of Fair Trade certified products (under FLO International / Fairtrade International) have grown exponentially. Today, there are over 1.2 million FT-certified farmers located in 66 different countries. Fair Trade products are now sold in over 120 countries (Fairtrade International, 2012).

The aim of this study is to provide an examination of the impacts of FT certification on producers. We begin by examining the universe of coffee mills in Costa Rica from 1999 to 2010. We find that FT certification is associated with higher export prices (approx. 5 cents per pound), but that there is no evidence that certification is associated with more sales

[1]Co-authored with Nathan Nunn

(either domestic or for export) or with higher domestic prices. This is not surprising since FT certification increases the price of coffee sold as Fair Trade – primarily exports – but does not itself guarantee increased sales. In addition, the fact that we do not see large increases in sales associated with FT certification provides some confidence that selection of 'better' coffee producers is not playing a large role. We also undertake a number of more formal tests of selection into certification. We do not find evidence of certification being spurred by increased sales, exports, or prices.

Having examined the effects of FT certifications at the producer level, we then turn to an examination of broader impacts of Fair Trade certification by linking our information on the locations of FT-certified mills to individual-level survey data. We construct a canton (i.e., district) level measure of FT intensity (i.e., share of production that is from FT certified producers) and examine the relationships between FT certification and individual incomes. Our analysis directly tests for differential benefits of FT certification for individuals employed in different parts of coffee production and those living in the area but not employed in coffee. We find that Fair Trade certification leads to an increase in average income for all households residing in the canton, but that the increase is concentrated only among the skilled coffee growers and farm owners. The majority of the workers in the coffee industry – who are those classified as unskilled or 'other' – do not see any benefits from Fair Trade. We also find some evidence of small positive spill-over effects for individuals not working in the coffee industry but living in cantons with Fair Trade certified coffee mills.

We also examine the impact of FT certification on the school attendance of children. Our estimates show that FT certification has no impact on elementary school attendance. We also find that FT certification is associated with lower school attendance among children of coffee unskilled coffee workers. This could be due to increased economic opportunities that arise due to FT certification, drawing children out of school and into the workforce. Although, we do not find evidence of increased wages from FT certifications for the vast majority of the workers, the increased wages to skilled coffee growers may be enough to induce children and young adult out of high school and university and into the coffee industry.

These findings provide valuable evidence of the impacts of FT certification for developing countries. To date, estimates of the impacts of Fair Trade remain limited. Existing studies primarily rely on cross-sectional analyses based on surveys of producers in a few developing countries. For example, Bacon (2005) presents the results of a survey of 228 coffee farmers in Nicaragua, and shows that the farmers who participated in FT and organic networks received higher average prices and reported feeling less concerned about losing their farm in the following year. A similar approach is employed by Becchetti and Constantino (2008) who base their analysis on a survey of 120 farmers in Kenya. Their results show that FT certification is associated with higher self-reported household consumption, more diversified production, and lower infant mortality. They find no relationship with child labor or investments in education. Ruben and Fort (2012) look at the impact of FT certification on coffee producers in Peru using data from a survey administered to six cooperatives, three of which were Fair Trade certified. They find no relationship between FT certification and household income or prices received. However, they do find that FT certification is associated with higher household expenditures, greater investments in land-attached infrastructure, better access to credit, and greater investments in organic and similar forms of specialized farming. In a second paper, Ruben et al. (2009) employ similar data-collection and empirical techniques to investigate the impact of FT on coffee and banana farmers in in Costa Rica and Peru. They find that FT certification is associated with slightly higher income but insignificant difference in expenditures, access to credit, or investment. Arnould et al. (2009) examine a cross-section of 1,269 coffee farmers from Nicaragua, Peru, and Guatemala. They find that in all three countries, Fairtrade certification is associated with greater sales, higher prices, and higher incomes.

One shortcoming of the existing evidence is that it relies on cross-sectional correlations. In addition, spill-overs and the distributional impacts of FT certification are not examined. Our study aims to improve upon the existing evidence by examining a panel of individuals and coffee producers, by estimating differential impacts for coffee workers involved in different parts of the production process, and by allowing for the existence of spill-over benefits to those not working in the coffee industry.

The paper is organized as follows. In the following section, we provide background information about Fair Trade certification and coffee production in Costa Rica. In section 3.3, we examine effects at the mill-level and test for selection into certification. In section 3.4, we then examine the impacts of FT certification at the household level, examining effect on adult incomes and school attendance of children. Section 3.5 concludes.

3.2 Background

3.2.1 Fair Trade Certification Generally

Fair Trade has its origins in an initiative started in Netherlands by a church-based NGO in 1988 in response to low coffee prices. The stated aim of the initiative was to ensure growers were provided "sufficient wages". The NGO created a fair trade label for their products, Max Havelaar, after a fictional Dutch character who opposed the exploitation of coffee pickers in Dutch colonies. Over the next half decade, Max Havelaar was replicated in other European countries and North America, and similar organizations, such as TransFair, emerged. In 1997, the various labeling initiatives formed an umbrella association Fair Trade Labelling Organization International (FLO) along with three other organizations (including TransFair). The FT Certification mark was launched in 2002.

The stated goal of Fair Trade is to improve the living conditions of farmers in developing countries. In practice, this is accomplished through two primary mechanisms: a guaranteed *minimum price* for coffee sold and a *price premium* that is paid. Both are set by Fair Trade Labelling Organization (FLO). For coffee producers, the minimum guaranteed price (for conventional Arabica washed coffee) is \$1.40 per pound and the premium is \$0.20 per pound.[2]

The minimum price is meant to cover the average costs of sustainable production, and acts as a price floor that reduces the risk faced by coffee growers. FT buyers must pay

[2] The minimum price for organic coffee is \$0.30 more and for unwashed coffee is \$0.05 less.

producers at least the minimum price when the world price is lower, and must pay the higher price when world price is above the FT minimum price. For the much of the past two decades the price floor has been binding, although not since about 2006.

The guaranteed premium for coffee sold as FT must be set aside and invested in projects that improve the quality of life for producers and their communities. The specifics of how the premium is used must to be decided upon in a democratic manner by the producers themselves. Potential projects that could be funded with the FT premium include the building of schools and health clinics, offering instruction courses for members of the community, provision of educational scholarships, investments in community infrastructure, improvements in water treatment systems, conversion to organic production techniques, etc. Since 2011, five cents of the premium must be invested towards improving the quality and productivity of coffee.

For coffee to be sold under the FT mark, all actors in the supply chain, including importers and exporters, must obtain FT certification. On the production side, the certification is open to small farmer organizations and cooperatives that have a democratic structure, as well as commercial farms and other companies that employ hired labor (Fair Trade Foundation, 2012). The certification entails meeting specific standards that are set and maintained by FLO. An independent certification company FLO-CERT (which split from FLO International in 2004) is in charge of inspecting and certifying producers (Fair Trade Foundation, 2012).

For coffee, the FT compliance criteria focus on the social, economic and environmental development of the community. In terms of social development, the producer organization must have a democratic structure and transparent administration in place, and must not discriminate against its members. To satisfy the economic development criteria, organizations need to be able to effectively export their product and administer the premium in a transparent and democratic manner. The environmental development criteria are meant to ensure that the members work towards including environmental practices as an integral part of farm management, by minimizing or eliminating the use of certain fertilizer and pesticides and replacing them with natural, biological methods, as well as adopting practices that ensure the health and safety of the cooperative members and the entire community (Fair Trade Foundation, 2012). In the case of commercial plantations that employ a large number workers, the FT standards entail that hired workers are not children or forced workers, and are free to bargain collectively. Hired workers must be paid at least minimum wage in the respective region, and must be given a safe, healthy, and equitable environment (Fair Trade Foundation, 2012).

To obtain FT certification, producer organizations need to submit an application with FLO-CERT. If the application is accepted, the organization goes through an initial inspection process carried out by one of the FLO-CERT representatives in the region. If the minimum requirements are met, the organization is issued a certificate that is usually valid for a year. The certificate can be renewed following re-inspection. During the first few years inspection and certification were free of charge. However, since 2004 producer organizations must pay application, initial certification, and renewal certification fees.

3.2.2 Coffee Production in Costa Rica

Coffee-cultivation in Costa Rica began to flourish following independence from Spain in 1821. The first coffee plantation were situated in San Jose, the capital of Costa Rica today. The region surrounding the capital, the Central Valley region, continues to plays an important role in coffee production. The agro-climatic conditions in the area, and to a large extent in the country generally, are favorable for coffee cultivation: volcanic soils, high elevation, and a climate characterized by a wet/dry season, and warm temperatures that stay relatively constant throughout the year (Instituto del Cafe de Costa Rica, 2012).

Historically, the government encouraged the cultivation of coffee through various policies such as the delivery of free coffee-plants to growers, land concession to whomever was interested in cultivating coffee, exemption from paying taxes for coffee, and land titling for anyone who cultivated coffee for 5 years on wasteland (Instituto del Cafe de Costa Rica, 2012).

Today, with 1.575 million bags of coffee (weighing 60kg per bag) exported in 2010-2011, Costa Rica is the 10th largest exporter of Arabica coffee in the world, with Europe being its primary export market. Approximately, 4% of Costa Rica's rural workers are in the coffee industry.

Coffee tends to be cultivated on small plots in family farms. The Costa Rica Coffee Institute (*Instituto de Cafe*) estimates that there are approximately 50,631 coffee-producing families in Costa Rica, of which 92.3% produce less than 75 bags (of 60kg each) per year.

When the ripe coffee cherries are harvested (generally from September until January), coffee farmers deliver the cherries to a local mill (called *beneficio*) for further processing. The *beneficio* measures the volume of the cherries received and issues a receipt. Here the pulp of the cherries is removed and the beans are washed through wet-milling and the cherries are transformed into green coffee.

The mills then sell the coffee received from producers to either roasters or exporters. Exporting is done through specialized firms, and in many cases through the mill's own export arm. Wet-mills usually belong to farmer cooperatives.[3] In addition to coffee processing services, cooperatives also provide a range of services to their members such as the provision of agricultural supplies, technical assistance, marketing assistance, and credit.

Coffee processing and sales in Costa Rica are heavily regulated by the Instituto del Café de Costa Rica (ICAFE), a government agency created in 1933 to oversee the coffee-growing industry and to provide a market that is equitable and fair for all parties involved. Each transaction between the mill and the exporter or roaster must be registered and approved by ICAFE (even if the transaction is intra-firm). ICAFE checks all transaction prices to ensure that each is in line with international coffee prices based on coffee type, denomination and quality.

Prior to the sale of the coffee by the mill, the farmer receives an advance payment for the cherries based on the international coffee prices prevailing at the time. The final price

[3]Cooperative members generally take the cherries to be processed at their cooperative mill, although in principle they are free to sell their cherries to others mills.

for the cherries sold is not determined until later in the year when the mill has sold all its coffee. Historically, the advance payment represents approximately two thirds of the total payment to the producer received for the harvest.[4] Every 15 days, the mill must report to ICAFE the coffee received from each producer.

Mills must make payment adjustments every 3 months, according to the sales advancements made to the farmer and the new sales made. In November, after all the green coffee as been sold and the average price for the harvest is determined, mills must make final payments to the coffee growers, also known as liquidation payments. The final payment to the producer is the residual payment after approved expenses by the law to the other actors in the coffee production chain.

The amount of the final sales/export price received by the mill must be distributed as follows: 3.3% is allocated to the exporter, 14.9% is allocated to the mill (this includes 9% mill profit and 5.9% for mill expenses), 1.2% is allocated to ICAFE, and 0.5% is allocated to Fonecafe, which is an insurance fund established to protect farmers in the event of a coffee crisis. Therefore, the producer receives 80% of the total price.[5]

3.2.3 Anecdotal Evidence on Selection into Fair Trade Certification

An important question, particularly for our subsequent empirical analysis, is what affects the decisions of mills to become FT certified. If FT has benefits, why aren't all mills FT certified? To better understand the source of variation underlying FT certification, we undertook interviews with FT-certified cooperatives in August of 2012. The interviews revealed a number of factors that underlie variation in certification status.

First, mills vary in the effective costs that FT requirements impose on the mill. For examples, several cooperatives mentioned the potential loss that they may suffer from being

[4] The mill obtains the funds for the producer advance payments from loans made by state banks, at a fixed exchange rate. In this way, the mill is exposed only to the fluctuation in the international price of coffee, while the bank has the exchange rate risk.

[5] The final liquidation prices for each mill must be published in Costa Rica's main newspapers in November, and the mill is obliged to pay the producer the balance of the payment within 8 days.

prevented from selling certain substances (mostly pesticides) in their stores. (Mills generally also operate a store where they sell various agricultural supplies to the community.) The extent to which a mill earns revenue from the sale of agricultural chemicals banned by FT affects its costs of certification. If this characteristics of mills is historically determined and varies little over time, it will be captured by mill fixed effects in our empirical analysis.

Second, the perceived benefits of FT certification also vary by mill. One of the primary benefits of FT sales is the existence of a guaranteed minimum price. The expected future benefit of this depends on the farmer's belief about future prices. Those farmers that expect the future world price for coffee to be above the minimum price perceive lower benefits to FT certification than farmers that believe future coffee prices may drop below the minimum. This variation is likely idiosyncratic or correlated with time-invariant characteristics that are captured by mill fixed effects.

Third, the farmer's beliefs also play an important role. Farmer's who a priori believe in the importance of environmentally sustainable or socially responsible farming practices will be more willing to undertake the changes in production dictated by FT certification. These beliefs, although they affect the timing of certification, are likely time-invariant and captured by mill fixed effects.

The fourth factor mentioned includes access to information regarding the logistics of becoming certified, and the costs and benefits of certification. Another factor along similar lines is the managerial ability needed to obtain and maintain certification. These last two factors potentially vary over time and may be correlated with other factors that also affect our outcomes of interest. For example, improvements in management or in international sales connections, may affect FT certification, but may also be associated with increased exports and prices.

3.3 Evidence from Mill-Level Data

We begin our analysis by examining the relationship between FT certification and outcomes measured at the mill/cooperative level. By examining what factors are changing for coffee producers that become FT certified, we are able to garner some evidence about the nature of selection into FT certification. If, for example, we find a surge in sales at the time when the producer becomes FT certified, then this provides evidence that economic conditions may be driving certification and potentially other outcomes of interest. Similarly, if we see a surge in exports, then this is evidence of foreign buyers (and access to a large foreign market) inducing selection into certification. Again, this potentially omitted factor could have an independent effect on our outcomes of interest.

The analysis combines two types of data. The first is information on coffee prices and quantities sold by mills and cooperatives. These data are obtained from ICAFE. For each mill, the ICAFE data contain total production (total coffee received for wet-milling from coffee growers in that year's harvest), broken down into the quantity exported and sold on the domestic market (measured in kilograms), and average prices obtained for the harvest in export and domestic markets for different types of coffee (conventional, differentiated, organic etc.).[6]

The second source of information we use is the FLO certification rosters, which contain the name and date of certification for all producer-organizations that have been certified since 2003. From these we extract the names of the coffee producer-organizations located in Costa Rica, and create an indicator variable for FT certification that equals one in the years in which the cooperative has the certification and zero otherwise. Since official certification rosters from FLO are not available to us before 2003, we have supplemented this with historical and archival research to identify mills that were FT certified between 1999 (the first year of our sample) and 2003. We match the certification indicator variable available from FLO with the ICAFE data, using the name of the producer organization as a common identifier. The matched data produces an unbalanced panel from 1999 until 2010, containing data for 262 coffee mills.

[6]The ICAFE data are recorded by harvest years (rather than calendar years), which range from October to October. In our data, an observation in year t corresponds to the harvest which is from October in year $t-1$ to October in year t.

We begin by estimating the following equation:

$$y_{i,t} = \alpha_i + \alpha_t + \beta_1 \cdot I^{FT}_{i,t} + \varepsilon_{i,t} \tag{3.1}$$

where i indexes a coffee mill and t years (1999–2010). $y_{i,t}$ denotes one of our outcomes of interest which we describe in more detail below. $I^{FT}_{i,c,t}$ is an indicator variable that equals one if mill i is FT certified in year t. α_i and α_t denote mill fixed effects and year fixed effects, respectively. As discussed, mill fixed effects control for time-invariant characteristics which may be correlated with the timing of FT certification.

We first estimate the relationship between FT certification and coffee sales, both domestic and foreign. The estimates are informative about the selection of firms into FT certification. For example, if firms that are prospering choose to become certified, then we expect to observe a relationship between FT certification and domestic (or total) sales. Similarly, if firms with increased export opportunities choose to become certified, then we expect to observe a relationship between FT certification and exports.

Estimates of equation (3.1) are reported in table 3.1. Columns 1, 3, and 5 report estimates with the natural log of domestic sales, exports and total sales as the dependent variable, respectively. The even numbered columns report analogous estimates, but controlling for a lagged dependent variable (LDV). The benefit of the inclusion of a LDV is that it accounts for the persistence of sales over time, possibly arising due to fixed costs. It is important to account for dynamics since past production may be associated with current certification status. A shortcoming of the estimates with a LDV is that because our regressions also includes mill fixed effects, they suffer from the Nickell bias. We, therefore, report estimates of equation (3.1) with and without a LDV.

We do not find evidence of statistically significant relationships between FT certification and increased sales, either domestically or internationally. Columns 7 and 8 examine exports as a share of total sales. We find no evidence that producers that are FT certified tend to export more.

Overall, there does not appear to be significant relationships between FT certification

Table 3.1: *The Effect of FT Certification on Producer Organizations: Quantities*

	Dependent variable:							
	ln domestic sales	ln domestic sales	ln exports	ln exports	ln total sales	ln total sales	Exports as a share of total sales	Exports as a share of total sales
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Fair Trade Certified, FTC	0.0441	0.0832	0.146	0.169	0.0489	0.0991	0.0404	0.0465
	(0.206)	(0.212)	(0.143)	(0.109)	(0.109)	(0.0985)	(0.0364)	(0.0321)
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Mill FE	Y	Y	Y	Y	Y	Y	Y	Y
Lagged dependent variable	N	Y	N	Y	N	Y	N	Y
Observations	1,182	909	1,187	921	1,220	950	1,220	950
Number of clusters/mills	194	235	194	235	194	235	194	235
R-squared	0.832	0.849	0.923	0.939	0.933	0.951	0.626	0.622

Notes: Coefficients are reported with standard errors clustered at the mill level in parantheses. All regressions include year fixed effects and mill fixed effects. ***, **, and * indicate significance ath the 1, 5, and 10 percent levels.

and the quantity of coffee sold. This is perhaps not surprising since FT certification does not directly provide a larger market for coffee producers. It only provides a guaranteed minimum price and a premium for coffee sold as Fair Trade.

The lack of a relationship between FT certification and quantities provides valuable evidence for the importance of selection into FT certification. If it was the most successful producers that selected into certification, then we would expect positive and statistically significant relationships between certification and sales. We do not observe this in the data.

We next turn to the relationship between FT certification and prices. Given that the stated intention of FT certification is to provide higher prices to certified producers, we do expect a positive relationship with prices.

Estimates are reported in table 3.2. Again the odd numbered columns do not include a LDV while the even numbered columns do. Columns 1–8 provide estimates of both average domestic prices and average export prices. Because of noisy price data, we have a number of large influential observations. We address this by reporting estimates using winsorized price data (at the 95th percentile) and using the natural log of prices.

As shown in columns 1-4, we estimate no statistically significant relationship between

Table 3.2: *The Effect of FT Certification on Producer Organizations: Prices*

	Dependent variable:							
	Domestic price (colon/lb)	Domestic price (colon/lb)	ln domestic price	ln domestic price	Export price (USD/lb)	Export price (USD/lb)	ln export price	ln export price
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Fair Trade Certified, FTC	18.81	9.737	0.0458	-0.00663	0.0386**	0.0399**	0.0508*	0.0497*
	(12.66)	(14.42)	(0.0473)	(0.0633)	(0.0195)	(0.0158)	(0.0296)	(0.0267)
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Mill FE	Y	Y	Y	Y	Y	Y	Y	Y
Lagged dependent variable	N	Y	N	Y	N	Y	N	Y
Observations	1,182	909	1,182	909	1,186	919	1,186	919
Number of clusters/mills	194	235	194	235	194	235	194	235
R-squared	0.946	0.949	0.933	0.935	0.935	0.939	0.922	0.929

Notes: Coefficients are reported with standard errors clustered at the mill level in parantheses. All regressions include year fixed effects and mill fixed effects. ***, **, and * indicate significance ath the 1, 5, and 10 percent levels.

domestic prices and FT certification. This is not surprising given that the vast majority of coffee sold as FT certified is exported and not sold domestically. The estimates reported in columns 5-8 show that we do find a positive and statistically significant relationship between FT certification and the export price. According to the estimates certification is associated with a price that is 4 cents per pound higher or about 5% higher.[7]

The estimated price impact may seem low given that the price premium alone during this period was either 10 or 20 cents per pound. However, it is important to keep in mind that producers in general are unable to sell all of their coffee under the FT label, even though it qualifies for certification. The supply of FT certified coffee is much greater than the demand. Therefore, FT certified farmers typically sell a large proportion of their coffee as conventional.[8]

As a further test of selection into FT certification, we examine whether there are observable producer characteristics that explain the onset of Fair Trade certification. In particular,

[7]These estimates are broadly consistent with Ronchi's (2002) estimated FT price impacts of 3% (exclusive of the FT premium) for 1998–2002. This was based on fieldwork undertaken with nine COOCAFE cooperatives.

[8]For a discussion on over-certification and free entry into Fair Trade and its impacts see Janvry et al. (2012).

we are interested in whether we see a significant increase in production, exports or sales prices, just prior to the onset of FT certification. If so, then this is evidence that an omitted factor, like a new contract to supply an overseas buyer, is causing the producer to become certified and may also be driving our other outcomes of interest, like prices, incomes, children's education, etc.

We examine this by estimating a variant of equation (3.1) but where the dependent variable is an indicator if period t is the first year that producer i is Fair Trade certified. We consider two sets of observable predictors. The first set is the value of domestic sales, exports, total sales, domestic prices, and export prices in the previous year. This tests whether the onset of certification was preceded by abnormally high levels of production, exports, or sales prices. Similarly, we also consider the growth rate of these variables in the previous two years (e.g., between periods $t-2$ and t). This checks whether the onset of certification is preceded by exceptionally high rates of growth in sales, exports, or prices.

The estimates are reported in table 3.3. Panel A reports the coefficients for the lagged levels variables and panel B the coefficients for the two-year growth variables. For both, we are interested in whether we observe a positive relationship between the independent variables and the onset of certification, since this is evidence of positive selection into certification. We find no evidence of such an effect. All twelve reported coefficients are not statistically different from zero, with very small point estimates. In addition, most coefficients are negative rather than positive. In particular, all three sales variables – domestic, exports, and total sales – have negative coefficients, suggesting that certifications tend to be preceded by lower than average sales and lower than average growth in sales.

Overall, the producer-level estimates provide no evidence for positive selection of producers into FT certification. FT certification is associated with higher export prices and their magnitudes can be accounted for by the FT premium. In addition, we find that FT certification is not associated with higher domestic prices, or greater quantities sold. We also do not find evidence that the onset of certification is preceded by better firm performance measures by levels or growth of sales, exports, or prices.

Table 3.3: *Determinants of FT Certification*

	Dependent variable: Indicator for the onset of FT certification					
	Characteristic for independent variable:					
	ln domestic sales	ln exports	ln total sales	Exports as a share of total sales	ln domestic price	ln export price
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: Certification onset and lagged characteristics					
One year lagged characteristic	-0.00056	-0.00639	-0.00634	-0.00557	0.0102	0.0313
	(0.00184)	(0.00436)	(0.00449)	(0.00917)	(0.0125)	(0.0522)
Year FE, Mill FE	Y	Y	Y	Y	Y	Y
Observations	949	949	971	971	949	948
R-squared	0.141	0.139	0.139	0.138	0.142	0.139
	Panel B: Certification onset and 2-year growth of characteristics					
Prior 2-year growth (*t*-2 to *t*)	-0.00222	-0.00081	-0.00570	0.0176	0.0139	0.0730
	(0.00198)	(0.00310)	(0.00373)	(0.0123)	(0.0158)	(0.0563)
Year FE, Mill FE	Y	Y	Y	Y	Y	Y
Observations	721	733	753	753	717	720
R-squared	0.160	0.158	0.158	0.158	0.171	0.175

Notes: Coefficients are reported with standard errors clustered at the mill level in parantheses. All regressions include year fixed effects and mill fixed effects. The dependent variable is an indicator variable that equals one in the first year of Fair Trade certification. The independent variable reported in Panel A is the lag of the characteristic reported in the column heading. The independent variable in panel B is the growth of the characteristic from period *t*-2 to period *t*. ***, **, and * indicate significance ath the 1, 5, and 10 percent levels.

3.4 FT Certification and Individual-Level Outcomes

3.4.1 Data and Estimating Equations

Our analysis begins uses the combined ICAFE and FLO mill-level data used in the previous section. Recall that for each mill/cooperative, we know total production, disaggregated into the quantity exported and the quantity sold domestically, and average prices for both exports and domestic sales.

To investigate the effect of FT certification on individual-level outcomes, such as employment, income, education, and community participation, we link the matched ICAFE-FLO data with household survey data from *Encuesta Hogares de Propositos Multiples (EHPM)*. EHPM has been carried out in July of each year since 1981. The survey contains information on individual and household incomes, education, community participation, durable goods ownership, etc. During our period of analysis, 2003–2009, the survey includes between 43,000–48,000 individuals per year.

We link the two data sources using the canton in which the individual lives and the canton of the mill/cooperative. The canton is the secondary administrative level (Costa Rica has 81 cantons). We obtain information of the canton of each mill from the address recorded by ICAFE. In the few cases where the address of the mill is not available from ICAFE, we obtained the information by contacting the mill directly.[9]Because harvested coffee cherries immediately begin to decompose and ferment, compromising the quality of the coffee, harvesting and processing occur within a 24 hour period. Given this characteristic of coffee, the locations of farms and the mills are almost always within the same canton.

Our primary variable of interest is a measure of FT certification intensity in a canton c in year t, which we denote with FTI_{ct}. The measure is the share of exports from in a canton and year that are from FT certified producers. Our measure relies on the assumption that the coffee received by a mill comes from coffee growers residing in the same canton as the mill, an assumption that we feel is valid. The measure we construct is the fraction of total

[9]We are able to identify the canton for over 90% of mills.

exports in a canton that are sold by Fair Trade certified producers.[10] More precisely, let X_{kct} denote total coffee exports in year t by producer-association k located in canton c, and let I^{FT}_{kct} be an indicator variable that equals one if producer k is FT certified in year t. Our measure of FT intensity of canton c in year t, FTI_{ct}, is given by:

$$FTI_{ct} = \sum_k \frac{X_{kct} \cdot I^{FT}_{kct}}{X_{kct}}. \tag{3.2}$$

A map showing the Fair Trade certification intensity across cantons in 2003 and 2009 is provided in figure 3.1. Cantons with no coffee production are shown in grey. Of the 81 cantons in Costa Rica, 45 do not produce coffee during our sample period.[11] For the 36 cantons with coffee production, the value of FTI_{ct} is represented with colors shades between yellow (low) and red (high).

Variation in FTI_{ct} is from two sources: existing or new mills obtaining FT certification and existing FT certified mills increasing exports relative to non-FT certified mills.

As explained, we combine the FT intensity measure with the *EHPM* household survey data, linking households to Fair Trade intensity by their canton. Thus, our first estimating equation is given by:

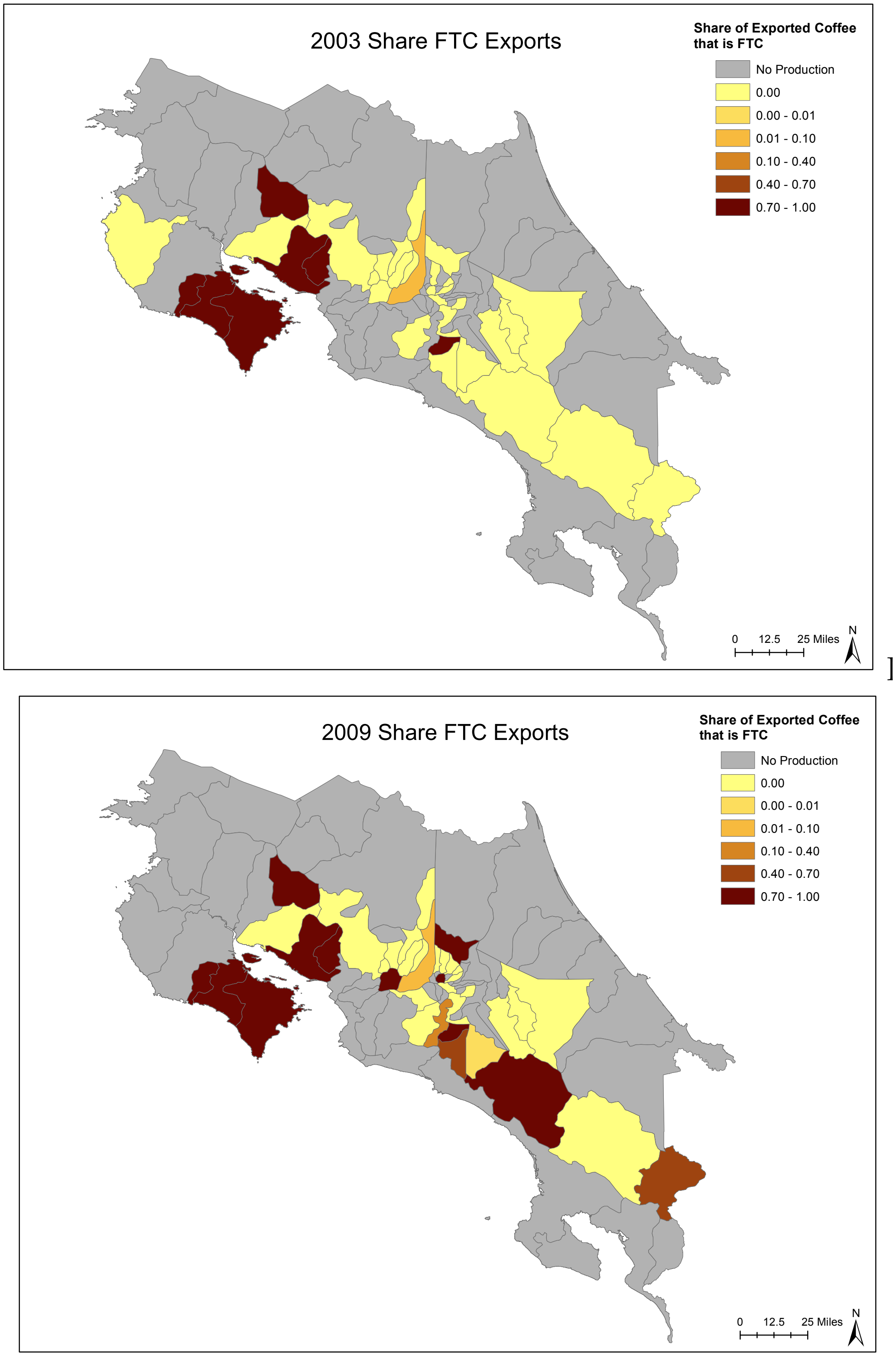
$$y_{j,i,c,t} = \alpha_i + \alpha_c + \alpha_t + \gamma_c Year_t + \beta_1 FTI_{c,t} + \beta_2 FTI_{c,t} \cdot I_j^{i=\text{coffee}} + \mathbf{X}_{j,t}\mathbf{\Gamma} + \varepsilon_{j,i,c,t} \tag{3.3}$$

where j denotes individuals, i industries (480), c cantons, and t years (2003–2009). The dependent variable, $y_{j,i,c,t}$, indicates on of our outcomes of interest, which we describe in further detail below. $FTI_{c,t}$ is our measure, described above, of the extent of Fair Trade certification in canton c in year t. $\mathbf{X}_{j,t}$ is a vector of individual-level covariates: education fixed effects, age, age^2, gender, gender $\times$ age, and gender $\times$ age^2. The equation includes canton, time and industry fixed effects. The inclusion of canton fixed effects α_c controls for

[10] It is important to emphasize that our measure is not a measure of the share of exports that are sold as FT certified. Because we do not know sales of FT certified coffee and non-FT certified coffee by mill, we are unable to construct this measure. Among the four cooperatives we interviewed in 2012, the share of their total sales in the previous year that was sold as FT was 80, 53, 40, and 10%.

[11] As we explain below, all empirical results are robust to restricting the analysis to only include the 36 coffee producing cantons. In addition, results are robust to only examining the rural areas within these cantons.

Figure 3.1: *Share of coffee producers that are Fair Trade certified (weighted by total exports) in 2003 and 2009.*



time-invariant regional characteristics that affect the outcomes. Time-fixed effects α_t control for macroeconomic shocks that are common to all industries and regions (coffee-producing regions). Industry fixed effects α_i control for time-invariant industry characteristics. Finally, we also include canton-specific linear time trends, $\gamma_c Year_t$, which capture differential trends in cantons over time, which may be correlated with certification.

Although it is likely that many of the benefits of FT spillover to all individuals within a region, it is also likely that the benefits are greatest for individuals working directly within the coffee industry. Equation (3.3) allows for this differential effect. The variable $I_j^{i=\text{coffee}}$ is an indicator variable that equals one if individual j's reported industry is "cultivation of coffee". Therefore, the coefficient β_2 measures the additional impact FT certification has on individuals directly involved in the coffee industry. The total effect on these individuals is given by $\beta_1 + \beta_2$. Because β_1 measures the effect of increasing FT intensity within a region on individuals not working in the coffee industry, it can be interpreted as the spillover effect of increasing FT certification within that region.

Even within the coffee industry, it is possible that workers benefit differentially from FT certification. For example, the farm owners may benefit differently than the unskilled coffee pickers that are hired seasonally. Therefore, we examine the distribution of benefits of FT certification with an estimating equation that distinguishes between three different workers within the coffee industry. These are workers that are defined as being skilled agricultural workers, unskilled agricultural workers, and all other workers involved in the coffee industry. In practice, we augment equation ((3.3)) by adding an occupation dimension and allowing for a differential impact of FT certification to those in the coffee industry depending on their occupation.

The augmented estimating equation is:

$$\begin{aligned}\ln y_{j,i,o,c,t} &= \alpha_{i,o} + \alpha_c + \alpha_t + \gamma_c Year_t \\ &+\beta_1 FTI_{c,t} + \beta_2 FTI_{c,t} \cdot I_j^{i=\text{coffee},o=\text{unskilled}} \\ &+\beta_3 FTI_{c,t} \cdot I_j^{i=\text{coffee},o=\text{skilled}} + \beta_4 FTI_{c,t} \cdot I_j^{i=\text{coffee},o=\text{other}} \\ &+\mathbf{X}_{j,t}\mathbf{\Gamma} + \varepsilon_{j,i,o,c,t} \end{aligned} \quad (3.4)$$

where o indexes a workers occupation (413), and $\alpha_{i,o}$ indicate occupation-industry fixed effects. $I_j^{i=\text{coffee},o=\text{unskilled}}$ is an indicator if j is in coffee cultivation and has an unskilled occupation, such as "coffee picker" and "agricultural laborers"; $I_j^{i=\text{coffee},o=\text{skilled}}$ is an indicator if j is in coffee cultivation and has a skilled occupation (or is owner), such as "farmers", "growers" and "skilled workers" and $I_j^{i=\text{coffee},o=\text{other}}$ is an indicator if individual j is in coffee cultivation and has an 'other' occupation, such as "farm administrator", "farm foreman", "plantation guard", "coffee taster", "driver", etc.

The inclusion of the double interaction terms allow the impact of FT production in a canton to be different for unskilled, skilled and other occupations in the coffee industry. The coefficients β_2, β_3, and β_4 measure the differential impact of FT production on the outcomes of individuals involved in the coffee industry for each of the three categories defined above. The industry-occupation FEs $\alpha_{i,o}$ capture the baseline coefficients for $I_j^{i=\text{coffee},o=\text{unskilled}}$, $I_j^{i=\text{coffee},o=\text{skilled}}$, and $I_j^{i=\text{coffee},o=\text{other}}$.

An alternative estimation strategy is to explicitly include the double interactions (e.g., $FTI_{d,t} \cdot I_j^{i=\text{coffee}}$, $FTI_{d,t} \cdot I_j^{o=\text{skilled}}$) by estimating the following equation:

$$\begin{aligned}\ln y_{j,i,o,c,t} &= \alpha_{i,o} + \alpha_c + \alpha_t + \gamma_c Year_t \\ &+\beta_1 FTI_{c,t} \cdot I_j^{o=\text{unskilled}} + \beta_2 FTI_{c,t} \cdot I_j^{i=\text{coffee},o=\text{unskilled}} \\ &+\beta_3 FTI_{c,t} \cdot I_j^{o=\text{skilled}} + \beta_4 FTI_{c,t} \cdot I_j^{i=\text{coffee},o=\text{skilled}} \\ &+\beta_5 FTI_{c,t} \cdot I_j^{o=\text{other}} + \beta_6 FTI_{c,t} \cdot I_j^{i=\text{coffee},o=\text{other}} \\ &+\mathbf{X}_{j,t}\mathbf{\Gamma} + \varepsilon_{j,i,o,c,t} \end{aligned} \quad (3.5)$$

This specification allows both the within-coffee impact and the outside-of-coffee spillover effect to differ depending on occupation (in this case differentially for unskilled agricultural workers). The coefficient β_3 measures the differential spillover effect of FT production on unskilled individuals within a district, while β_4 measures the additional impact of FT certification on unskilled individuals in the coffee industry relative to unskilled individuals in other industries. The impact of FT production on unskilled workers not in the coffee industry is given by β_1, while the impact on unskilled workers in the coffee industry is given by $\beta_1 + \beta_2$. As in equation (3.4), in equation (3.5), the double interaction $I_j^{i=\text{coffee}} \cdot I_j^{o=\text{unskilled}}$ is absorbed by the industry-occupation fixed effects.

3.4.2 Results

We now turn to our estimation results, beginning first by examining the relationship between Fair Trade certification and average monthly income.

Incomes

Estimates of equations (3.3)–(3.5) are reported in table 3.4. Column 1 reports estimates of equation (3.3). The estimates indicate a small positive impact of FT certification within the canton. In addition, we estimate an additional positive impact for individuals working in the coffee industry. The combined coefficient for this group is 0.168 compared to 0.068 for those not in coffee.

The estimates of column 2 show that the average impact for those in coffee masks significant heterogeneity. The baseline impact to those not the coffee industry remains similar (0.070) in column 2, although it is no longer statistically significant. In addition, there is no additional benefit to being an unskilled coffee worker. In fact, the combined effect of FT certification for these workers is very close to zero: $0.070 - 0.082 = -0.012$. By contrast, there is an additional benefit to skilled coffee growers. The combined benefit of FT certification is: $0.070 + 0.329 = 0.399$. For all other workers, again the combined benefit of FT certification is not statistically different from zero: $0.070 - 0.224 = 0.154$.

Table 3.4: *The Effect of FT on Incomes by Industry and Occupation.*

	Sample: Adults in all districts					
	Dependent variable: ln individuals' avg monthly income					
	(1)	(2)	(3)	(4)	(5)	(6)
Fair Trade Intensity, FTI	0.063**	0.068		0.161*	0.123	
	(0.031)	(0.050)		(0.082)	(0.079)	
FTI x Coffee	0.124			0.110		
	(0.094)			(0.096)		
FTI x Coffee x Skilled		0.334**	0.434**		0.320**	0.421**
		(0.144)	(0.165)		(0.149)	(0.169)
FTI x Skilled			-0.035			0.018
			(0.098)			(0.121)
FTI x Coffee x Unskilled		-0.059	-0.052		-0.071	-0.065
		(0.092)	(0.101)		(0.092)	(0.101)
FTI x Unskilled			0.055			0.110
			(0.068)			(0.092)
FTI x Coffee x Other		-0.205	-0.215		-0.225	-0.235
		(0.150)	(0.149)		(0.153)	(0.152)
FTI x Other			0.075			0.131*
			(0.050)			(0.079)
Age, age2, gender & interactions	Y	Y	Y	Y	Y	Y
Education controls	Y	Y	Y	Y	Y	Y
81 District FE	Y	Y	Y	Y	Y	Y
7 Year FE	Y	Y	Y	Y	Y	Y
10,195 Industry x Occupation FE	N	Y	Y	N	Y	Y
480 Industry FE	Y	N	N	Y	N	N
District-specific time trends	N	N	N	Y	Y	Y
Observations	112,643	112,643	112,643	112,643	112,643	112,643
Clusters	79	79	79	79	79	79
R-squared	0.518	0.607	0.607	0.519	0.608	0.608

Notes: The unit of observation is an individual. The dependent variable is the natural log of annual income. Coefficients are reported with standard errors clustered at the district level. All regressions include education FE, district FE, year FE, and controls for age, age-squared, gender, gender x age, and gender x age-squared. Column 1 also controls for industry fixed effects, while columns 2-5 control for industry x occupation fixed effects. ***, **, and * indicate significance at the 10, 5 and 1 percent levels.

The finding of a large benefit to FT certification for skilled coffee growers, but not for other workers is confirmed in the estimates of equation (3.5) reported in columns 3-5.

The magnitudes of the estimated effects are sizeable. Consider the impact for skilled coffee growers. According to the estimates, an increase in FT intensity from 0 to 0.10 (approximately the sample mean) is associated with increase incomes by 40%. This is a very significant increase.

Overall, the estimates indicate that there are benefits of FT certification, but that these benefits are unevenly distributed among those within the coffee industry. While the owners of the coffee farms and their high-skilled workers received higher incomes from certification, there is no evidence that the other workers, including unskilled coffee pickers benefit in any way.

Our findings are not surprising once one considers the structure of FT. Unless the members of the cooperative (likely the 'skilled workers' in our sample) decide to allocate some of the premium to increasing the wages of coffee pickers and other hired workers (unskilled and 'other' workers in our sample), we should not expect to see any income effects for this group of workers from increasing FairTrade production. Our findings are also consistent with descriptive evidence from Valkila and Nygren (2009) indicating that Guatemalan coffee workers do not appear to benefit from Fair Trade.

In the sample, "other" occupations account for about 7% of all workers in the coffee industry, "unskilled" occupations account for 50%, and "skilled" occupations account for 43%. Therefore, in terms of overall impacts, it is important to keep in mind that the positive effects are felt among slightly less than half of coffee workers, while the majority of workers (57%) felt no impact.

In table 3.5, we test the robustness of our estimates by restricting the sample in a number of different ways. We first restrict the sample to only include: (*i*) cantons that produce coffee (36 in total), and (*ii*) rural areas of these coffee producing cantons. One could argue that these provide more comparable samples, since it is possible that individuals living in urban areas and/or in cantons that are uninvolved in coffee are irrelevant for our analysis. Estimates of equation (3.4) for these two subsample are reported in columns 3 and 5 (column 1 reproduces the baseline estimates for comparison). We also check the robustness of our estimates to only examining the incomes of household heads. We do this separately for all three samples: all cantons, coffee producing cantons, and rural parts of coffee cantons. The estimates are reported in columns 2, 4, and 6 of table 3.5.

The auxiliary estimates reported in table 3.5 confirm the estimates from table 3.4. The estimated impacts are very similar. We continue to find a link between FT certification and higher incomes, but only for skilled coffee growers. The estimated magnitudes are also very similar to the baseline estimates.

One difference between the specifications is that when we restrict the sample to the rural

Table 3.5: *The Effect of FT on Incomes: Robustness to subsamples*

	All districts		Coffee producing districts only		Rural parts of coffee producing districts	
	All individuals	Household heads only	All individuals	Household heads only	All individuals	Household heads only
	(1)	(2)	(3)	(4)	(5)	(6)
Fair Trade Intensity, FTI	0.123	0.189	0.105	0.170	0.139	0.256
	(0.079)	(0.141)	(0.072)	(0.123)	(0.104)	(0.173)
FTI x Coffee x Skilled	**0.320****	**0.347****	**0.317****	**0.340****	**0.351****	**0.382****
	(0.149)	**(0.133)**	**(0.151)**	**(0.139)**	**(0.157)**	**(0.145)**
FTI x Coffee x Unskilled	-0.071	-0.092	-0.071	-0.104	-0.053	-0.073
	(0.092)	(0.101)	(0.095)	(0.102)	(0.094)	(0.104)
FTI x Coffee x Other	-0.225	-0.193	-0.104	-0.029	-0.090	-0.078
	(0.153)	(0.152)	(0.213)	(0.198)	(0.233)	(0.225)
Age, age2, gender & interactions	Y	Y	Y	Y	Y	Y
District FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Industry x Occupation FE	Y	Y	Y	Y	Y	Y
District-specific time trends	Y	Y	Y	Y	Y	Y
Observations	112,643	60,315	56,203	29,706	33,261	18,515
Clusters	79	79	36	36	36	36
R-squared	0.608	0.622	0.629	0.647	0.621	0.634

Notes: The unit of observation is an individual. Coefficients are reported with standard errors clustered at the district level. All regressions include district FE, industry-occupation fixed effects, year fixed effects, and controls for age, age-squared, gender, gender x age, and gender x age-squared. ***, **, and * indicate significance at the 10, 5 and 1 percent levels.

parts of coffee producing cantons, we estimate a larger positive and statistically significant impact of FT certification to all individuals in the area. This is as expected, since this subsample is the group that is most likely to be impacted by the spillover benefits from FT certification, such as subsidies to education, the building of infrastructure, etc.

It is unclear whether the full sample or subsamples are preferred. Although the smaller samples remove observations that are arguably irrelevant to the impacts of FT certification, their inclusion does help to more precisely estimate covariates in the regression equation, like the industry-occupation fixed effects, year fixed effects, and the coefficients on gender and age (as well as their interactions). Throughout the rest of the paper we report estimates from the full sample. All of our results are robust to using any of the subsamples reported in table 3.5.

We also check the robustness of our estimates to the use of different Fairtrade intensity measures. The estimates are reported in table 3.6. Column 1 reproduces the baseline estimate that uses exports to create an export weighted measure of FT intensity. In column 2 reports estimates using production weights. As shown, the estimates are nearly identical. Next, we use time-invariant export weights. In other words, in equation (3.2), we use $\overline{X}_{kc}$ rather than X_{kct}, where $\overline{X}_{kc}$ is average exports of mill k in canton c between 2003 and 2010. There is a potential concerned with the variation in FTI arising from the year-to-year change in exports across mills. This measure, by using a time-invariant measure of exports, is purged of this variation. As shown in column 4, the estimates remain robust. In column 5, we report similar estimates, but using exports in the initial period, 2003, rather than average exports as weights. Again, the estimates remain robust. In the last robustness check we construct an extremely coarse measure of FTI that is completely independent of any cross-sectional or time series variation in production or exports. We use an indicator variable that equals one if there is at least one Fair Trade certified mill in the canton in that year. As shown, the results are robust the use of this coarse measure of Fair Trade intensity.

It is possible that although FT certification does not impact the wages of unskilled and 'other' workers in the coffee industry, it does increase the number of workers hired. We check for this by estimating equations (3.3)–(3.5), but with the dependent variable being an indicator variable for employment (either full or part time). This tests whether coffee workers in districts with more FT certified coffee production are more likely to have a job – i.e., less likely to be unemployed.

The estimates are reported in table 3.7. We find no evidence of that FT certification increases employment. All of the coefficients of interest are close to zero and statistically insignificant.

An important caveat about these estimates is that they rely on the assumption that unemployed workers have a well-defined occupation and industry. In reality this may not be the case. In the data, for 18.0 percent of the unemployed population either their industry or occupation is listed as missing. For employed individuals, the same data are missing for only 0.17 percent of the sample.

Table 3.6: *The Effect of FT on Incomes: Robustness to using alternative FTI measures*

	Fair Trade Intensity Measure Used:				
	Baseline: export weighted	Production weighted	Time invariant export weights	Initial (2003) export weights	Indicator if at least on mill is FT certified
	(1)	(2)	(3)	(4)	(5)
Fair Trade Intensity, FTI	0.123	0.124	0.111**	0.104**	0.074**
	(0.079)	(0.075)	(0.055)	(0.040)	(0.034)
FTI x Coffee x Skilled	**0.320****	**0.317****	**0.240***	**0.199***	**0.178***
	(0.149)	**(0.155)**	**(0.126)**	**(0.115)**	**(0.093)**
FTI x Coffee x Unskilled	-0.071	-0.066	-0.062	-0.054	-0.002
	(0.092)	(0.095)	(0.082)	(0.079)	(0.072)
FTI x Coffee x Other	-0.225	-0.220	-0.149	-0.131	-0.155*
	(0.153)	(0.158)	(0.134)	(0.121)	(0.092)
Age, age2, gender & interactions	Y	Y	Y	Y	Y
District FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Industry x Occupation FE	Y	Y	Y	Y	Y
District-specific time trends	Y	Y	Y	Y	Y
Observations	112,643	112,643	112,643	112,643	112,643
Clusters	79	79	79	79	79
R-squared	0.608	0.608	0.608	0.608	0.608

Notes: The unit of observation is an individual. Coefficients are reported with standard errors clustered at the district level. All regressions include district FE, industry-occupation fixed effects, year fixed effects, and controls for age, age-squared, gender, gender x age, and gender x age-squared. ***, **, and * indicate significance at the 10, 5 and 1 percent levels.

Table 3.7: *The Effect of FT on Employment*

	Sample: Adults in the labor force					
	Dependent variable: Employment indicator variable					
	(1)	(2)	(3)	(4)	(5)	(6)
Fair Trade Intensity, FTI	0.003	0.004		0.026**	0.028**	
	(0.006)	(0.008)		(0.013)	(0.013)	
FTI x Coffee	0.012			0.011		
	(0.015)			(0.014)		
FTI x Coffee x Skilled		-0.002	-0.009		-0.005	-0.013
		(0.010)	(0.010)		(0.010)	(0.010)
FTI x Skilled			0.011			0.037***
			(0.007)			(0.012)
FTI x Coffee x Unskilled		0.014	0.005		0.012	0.003
		(0.025)	(0.026)		(0.024)	(0.025)
FTI x Unskilled			0.013			0.038**
			(0.014)			(0.017)
FTI x Coffee x Other		-0.059	-0.057		-0.060	-0.058
		(0.080)	(0.080)		(0.079)	(0.080)
FTI x Other			0.003			0.027**
			(0.008)			(0.013)
Age, age2, gender & interactions	Y	Y	Y	Y	Y	Y
Education controls	Y	Y	Y	Y	Y	Y
81 District FE	Y	Y	Y	Y	Y	Y
7 Year FE	Y	Y	Y	Y	Y	Y
10,195 Industry x Occupation FE	N	Y	Y	Y	Y	Y
480 Industry FE	Y	N	N	N	N	N
District-specific time trends	N	N	N	Y	Y	Y
Observations	123,242	123,242	123,242	123,242	123,242	123,242
Clusters	79	79	79	79	79	79
R-squared	0.044	0.130	0.130	0.045	0.131	0.131

Notes: The unit of observation is an individual. The dependent variable is an indicator variable if an individual is employed (either full or part time) and in the labor force. Coefficients are reported with standard errors clustered at the district level. All regressions include education FE, district FE, year FE, and controls for age, age-squared, gender, gender x age, and gender x age-squared. Column 1 also controls for industry fixed effects, while columns 2-5 control for industry x occupation fixed effects. ***, **, and * indicate significance at the 10, 5 and 1 percent levels.

3.4.3 Children's Education

We next turn to an investigation of effects of FT certification on education. There are three main channels through which FT production could impact education. First, by increasing household incomes, FT certification may increase educational attainment. As we have seen, FT certification is associated with higher payments to skilled workers in the coffee industry, as well as a spillover to the incomes of other individuals residing in the same the canton. Second, Fair Trade certification, by making coffee production a more profitable endeavor, may increase the opportunity costs of going to school. We expect this to be particularly relevant for university-aged children. This is an effect has been found in other developing-country contexts (Atkin, 2012). Third, FT could affect educational attainment through enhanced provision of public goods in a region. As discussed, in Costa Rica, part of the Fair Trade premium is directed towards the building of schools, the provision of books, equipment and other materials, and the provision of scholarships for students to attend high school, university, and other classes. For example, since COOCAFE's creation of the Children of the Field Foundation (*Fundación Hijos del Campo*) in 1996, they have provided scholarships to 2,598 students and financial support to 240 schools. COOCAFE estimates that in all, over 5,800 students have been helped by their foundation.

To examine the impacts of FT certification on educational attainment, we estimate equation (3.4) among samples of children aged 7 to 12 years old (potential elementary school students), 13 to 17 (secondary school students) and 18 to 25 (university students). Rather than using the individuals' industries and occupations (as we did for the income regressions), we instead use the industry and occupation of the household head. This is because industry and occupation are undefined for children that are not employed. Thus, the estimates report how child school attendance varies with FT certification for households that are not in coffee production, and for households involved in different occupations within the coffee industry.

Estimates are reported in table 3.8 for elementary-aged children, secondary-aged children, and university-aged children respectively. The even numbered columns control for district-

Table 3.8: *FT Certification and School Attendance*

	Dependent variable: Indicator for school enrollment					
	Ages 7-12		Ages 13-17		Ages 18-25	
	(1)	(2)	(3)	(4)	(5)	(6)
Fair Trade Intensity, FTI	-0.003	-0.006	0.076**	0.063	-0.059**	-0.065
	(0.005)	(0.009)	(0.032)	(0.078)	(0.025)	(0.052)
FTI x Coffee x Skilled	0.022	0.021	-0.038	-0.047	-0.074	-0.071
	(0.023)	(0.024)	(0.109)	(0.107)	(0.057)	(0.058)
FTI x Coffee x Unskilled	0.022	0.023	**-0.217*** **	**-0.213** **	**-0.179** **	**-0.168***
	(0.027)	(0.025)	**(0.101)**	**(0.100)**	**(0.080)**	**(0.089)**
FTI x Coffee x Other	-0.001	-0.005	**-0.842*** **	**-0.837*** **	**-0.135**	**-0.106**
	(0.006)	(0.007)	**(0.165)**	**(0.166)**	**(0.143)**	**(0.135)**
Age, age2, gender & interactions	Y	Y	Y	Y	Y	Y
District FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Industry x Occupation FE (of hh head)	Y	Y	Y	Y	Y	Y
District-specific time trends	N	Y	N	Y	N	Y
Observations	35,174	35,174	30,653	30,653	41,431	41,431
Clusters	79	79	79	79	79	79
R-squared	0.090	0.095	0.249	0.255	0.305	0.309

Notes: The unit of observation is an individual. The dependent variable is an indicator variable if a child attends school. Coefficients are reported with standard errors clustered at the district level. All regressions include district fixed effects, year fixed effects, fixed effects for the household head's industry x occupation, and controls for age, age-squared, gender, gender x age, and gender x age-squared. The even numbered columns also include district-specific time trends.

specific time trends while the odd numbered columns do not. An interesting pattern emerges. First, as reported in columns 1 and 2, FT certification appears to have no impacts on attendance in elementary schools. This is consistent with the fact that elementary school attendance rates are very high in Costa Rica. For example, in our sample 99.2% of children aged 8 report being enrolled in school. Further, there is no indication that Fair Trade premiums are directed towards elementary schools.

By contrast, we do find evidence of impacts of FT certification on secondary school and University attendance. The estimates reported in columns 3–6 indicate that for children aged 13-17 and 18-25, if a household is directly involved in coffee production, then the impact of FT certification is estimated to be negative and robustly significant for unskilled workers. The negative estimate is large and significant for high school aged children (13-17) with parents involved in "other" occupations in the coffee industry.

The reason that FT certification is associated with lower school enrollment among children of unskilled and "other" coffee workers is not immediately obvious. It it potentially explained by greater employment opportunities that arise because of FT certification. This may sound perplexing given that we have seen that unskilled and 'other' do not receive higher wages due to FT certification. However, the increased wages earned by the skilled workers, may provide a potential future reward that induces children to drop out of school and enter the coffee industry. Another potential explanation is that FT certification does provide benefits to workers that are not captured by income, such as safer working conditions, more stability, better health and dental care, etc. Due to lack of data, our analysis does not test for these benefits of Fair Trade.

This line of reasoning does raise the question of why we do not observe a decline in attendance for children of skilled coffee workers, particularly since they are the ones that actually receive higher wages. Certainly, the expected increase to incomes must be greatest for this group. However, the explanation may lie in a counteracting effect of higher incomes. As has been shown in other developing-country contexts low incomes prevent parents from being able to send children to school. Edmonds et al. (2010) show this when examining

Table 3.9: *FT Certification, Education, and Employment: Ages 13-17*

	Sample: Individuals 13-17 years old				
	Attend School	Inactive	In labor force	Employed	Unemployed
	(1)	(2)	(3)	(4)	(5)
Fair Trade Intensity, FTI	0.063	-0.137*	0.147**	0.146**	0.001
	(0.078)	(0.074)	(0.070)	(0.058)	(0.015)
FTI x Coffee x Unskilled	-0.047	0.043	-0.037	-0.027	-0.010
	(0.107)	(0.104)	(0.100)	(0.094)	(0.018)
FTI x Coffee x Skilled	-0.213**	-0.012	0.003	0.003	-0.000
	(0.100)	(0.076)	(0.071)	(0.068)	(0.033)
FTI x Coffee x Other	-0.837***	-0.466***	0.455***	0.469***	-0.013
	(0.166)	(0.059)	(0.052)	(0.055)	(0.026)
Age, age2, gender & interactions	Y	Y	Y	Y	Y
36 District FE	Y	Y	Y	Y	Y
7 Year FE	Y	Y	Y	Y	Y
7,171 Industry x Occupation FE	Y	Y	Y	Y	Y
Observations	30,653	30,653	30,653	30,653	30,653
R-squared	0.255	0.261	0.256	0.237	0.138

Notes : The unit of observation is an individual. Coefficients are reported with standard errors clustered at the district level. All regressions include district FE, industry-occupation fixed effects, year fixed effects, district-specific time trends, and controls for age, age-squared, gender, gender x age, and gender x age-squared. ***, **, and * indicate significance at the 10, 5 and 1 percent levels.

the impacts of India's 1991 tariff reforms. Therefore, FT-induced increase in income may work as a counteracting force increasing school enrollment for this group. In other words, for children of parents in the coffee industry, higher incomes from FT induce children to drop out of school. But for children of parents that receive higher incomes from FT, this reduction is counteracted by an increase in enrollment due to higher incomes.

In an attempt to better understand the reason for the education results, we also examine the relationship between FT certification and the following alternative activities: being inactive, participating in the labor force, being employed, and being unemployed. Estimates are reported in tables 3.9 and 3.10 for children aged 13–17 and 18–25. Column 1 of the tables reproduce the education estimates of specification (3.3). Columns 2–4 of the tables report estimates where the dependent variable is an indicator for the individual being in the labor force (employed or unemployed), an indicator for being inactive, an indicator for employment, and an indicator for unemployment.

Consider first the estimates for 13–17 year old teenagers reported in table 3.9. The estimates show that the decline in school attendance for children of "other" coffee workers

Table 3.10: *FT Certification, Education, and Employment: Ages 18-25*

	Sample: Individuals 18-25 years old				
	Attend School	Inactive	In labor force	Employed	Unemployed
	(1)	(2)	(3)	(4)	(5)
Fair Trade Intensity, FTI	-0.065	-0.038	0.042	0.112**	-0.070***
	(0.052)	(0.058)	(0.046)	(0.050)	(0.019)
FTI x Coffee x Unskilled	-0.071	-0.064	0.104	0.025	0.079***
	(0.058)	(0.091)	(0.092)	(0.091)	(0.029)
FTI x Coffee x Skilled	-0.168*	0.027	-0.016	-0.121	0.104
	(0.089)	(0.114)	(0.115)	(0.101)	(0.088)
FTI x Coffee x Other	-0.106	0.258**	-0.258***	-0.252***	-0.006
	(0.135)	(0.106)	(0.092)	(0.092)	(0.023)
Age, age2, gender & interactions	Y	Y	Y	Y	Y
36 District FE	Y	Y	Y	Y	Y
7 Year FE	Y	Y	Y	Y	Y
7,171 Industry x Occupation FE	Y	Y	Y	Y	Y
Observations	41,431	41,431	41,431	41,431	41,431
R-squared	0.309	0.327	0.303	0.299	0.135

Notes: The unit of observation is an individual. Coefficients are reported with standard errors clustered at the district level. All regressions include district FE, industry-occupation fixed effects, year fixed effects, district-specific time trends, and controls for age, age-squared, gender, gender x age, and gender x age-squared. ***, **, and * indicate significance at the 10, 5 and 1 percent levels.

coincides with a decrease in children that are inactive and an increase of children in the labor force that are employed. There is no association with unemployment. This suggest that FT is associated with children being drawn from school and from an inactive status and moving into employment. The estimates also show that for children of parents not in coffee, FT coffee production in a canton is associated with a movement of children from inactivity into employment.

Next, consider the estimates for 18–25 year old youths reported in table 3.9. For children of parents that are "other workers" in coffee, we see that FT certification is associated with an increase in inactivity and a decline in employment. In other words, FT is associated with children dropping out of employment (or being force to drop out) and moving into inactivity. We also see some evidence of that FT is associated with an increase in unemployment for the children of unskilled coffee workers and a decrease in unemployment (and increase in employment) for children of those not in coffee.

3.5 Conclusion

Our analysis has provided evidence, taken from coffee production in Costa Rica, that Fair Trade certification can have impacts in developing countries. However, our analysis also showed that the benefits of Fair Trade may not be distributed to the poorest workers in the industry. Examining individual-level survey data, we found that Fair Trade certification is associated with increased incomes of a small group of skilled coffee growers and farm owners. For other workers in the coffee industry we find no evidence that FT certification increases income.

We also examined impacts on the education of children. We found that FT certification is associated with increased school attendance in the region. This is most likely due to the FT premium that is set aside for educational support and scholarships by FT certified producers. We also found evidence that FT certification is associated with lower school attendance among some children of coffee workers. This is likely due to increased economic opportunities that arise due to FT certification, drawing children out of school and into the workforce.

To gain further evidence on selection into certification and causal mechanisms, we moved to an examination of finer data at the producer level. We found that FT certification is associated with higher export prices (approx. 5 cents per pound), but that there is no evidence that certification is associated with more sales (either domestic or for export) or with higher domestic prices. This is consistent with expectations since FT certification increases the price of coffee sold as Fair Trade – primarily exports – while certification does not itself guarantee or attempt to directly generate increased sales. Further the fact that we do not see large increases in sales associated with FT certification provides some confidence that selection of 'better' coffee producers in 'better' regions is not playing a large part. We can therefore be more confident that the income and education estimates are close to causal estimates.

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